Grounded Multimodal Procedural Entity Recognition for Procedural Documents: A New Dataset and Baseline

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Abstract

Much of commonsense knowledge in real world is in the form of procudures or sequences of steps to achieve particular goals. In recent years, knowledge extraction on procedural documents has attracted considerable attention. However, they often focus on procedural text but ignore a common multimodal scenario in the real world. Images and text can complement each other semantically, alleviating the semantic ambiguity suffered in text-only modality. Motivated by these, in this paper, we explore a problem of grounded multimodal procedural entity recognition (GMPER), aiming to detect the procedural entity and the corresponding bounding box groundings in images (i.e., visual entities). A new dataset (Wiki-GMPER) is built and extensive experiments are conducted to evaluate the effectiveness of our proposed model.

Keywords: Multimodal Procedure Knowledge, Procedural Entity Recognition, Procedural Entity Grounded

1. Introduction

In our daily life, much of commonsense knowledge is in the form of sequences of actions to achieve particular goals (e.g., cooking recipes, crafting and maintenance manuals), which is called *Procedural Knowledge* (Georgeff and Lansky, 1986; Ren et al., 2023). For the large and growing amount of unstructured or semi-structured procedural documents on media platforms such as *WikiHow*[1], *EHow*[2] and *Instructables*[3], it is a pressing need to automatically extract procedural knowledge (e.g., entities or relations) for knowledge graph constructions and downstream procedures understanding applications (e.g., sequence ordering (Wu et al., 2022), question answering system (Zhang et al., 2022) and operation diagnosis (Luo et al., 2021)).

Generally, procedural documents often appear in a multimodal manner. As shown in Figure 1, each step in a procedural document contains an image and the corresponding text description. Nevertheless, current existing procedural entity recognition (PER) methods (Jermsurawong and Habash, 2015; Leopold et al., 2018; Mysore et al., 2019; Jiang et al., 2020; Luo et al., 2021) mainly focus on the text-only settings, which is insufficient for entity disambiguation (Yu et al., 2023). For example shown in Figure 1, without the red bounding box, it is difficult to refer to what state the procedural entity "*Tomato*" is in each step depending only on text description (e.g., a whole tomato in Step 1, while tomato slices in Step 3). Capturing the visual entities (e.g., the red bounding box in Figure 1) in images are beneficial for the procedural document understanding and reasoning (Wu et al., 2022; Zhang et al., 2022). Motivated by this, our work in this paper considers a multimodal setting where the multimodal procedural knowledge extraction system not only detects the procedural entities from the procedural text description but also links the procedural entities to their corresponding bounding boxes in images, as shown in Figure 1. The research on this subject can be called as *Grounded Multimodal Procedural Entity Recognition (GMPER)*.

To tackle the GMPER task, two kinds of related solutions, i.e., Multimodal Named Entity Recognition *MNER* (Zhang et al., 2018) and Grounded Multimodal Named Entity Recognition *GMNER* (Yu et al., 2023) are proposed to extract entities from social media posts. Specifically, existing MNER methods (Moon et al., 2018; Lu et al., 2018; Yu et al., 2020; Zhang et al., 2021a; Chen et al., 2022; Wang et al., 2022a; Jia et al., 2022, 2023) are designed to extract the textual entities with the help of visual features from images, but fail to build the link or correspondence between textual entities and visual entities. To solve this problem, Yu et al. 2023 propose a new task *GMNER*, aiming to simultaneously recognize the textual entities and the corresponding visual regions in images.

Though recent GMNER methods (Yu et al., 2023) achieve remarkable performance, but still face several main challenges when directly adapted to the GMPER task. Firstly, different from the GMNER task which mainly focuses on short multimodal posts, the GMPER task is based on long multimodal procedural documents with multiple steps

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[1]https://www.wikihow.com/Main-Page
[2]https://www.ehow.com/
[3]https://www.instructables.com/

LREC-COLING 2024, pages 7971–7981
20-25 May, 2024.

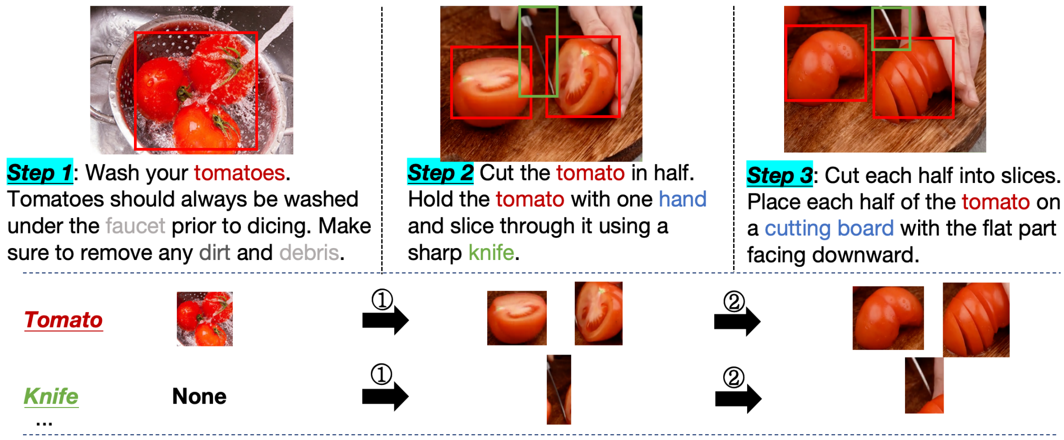


Figure 1: A Case of Grounded Multimodal Procedural Entity Recognition for the Multimodal Procedure document "How to Dice Tomatoes".

Figure 2: Two Cases of Object Detection by Grounded Language-Image Pretrained Model (GLIP) (Li et al., 2022) with the Prompt Text "Tomato or Persimmon"; The highest confidence score for cting object *"tomato"* in left image is **0.76**, while that in the right image is **0.57**.

and complex interactions between procedural entities. As shown in Figure 1, the same procedural entity has multiple visual regions with different states and meanwhile, there will be mutual occlusion between visual procedural entities. Secondly, the state of the same visual entity, such as shape, color and forms (e.g., solid, liquid and gaseous) will dynamically change as the procedure progresses. Existing *MNER* or *GMNER* methods only consider one descriptive text and the corresponding image. It is a challenge for them to track the state changes of visual entities between steps on multimodal procedural documents. For example shown in Figure 2, when the target object *"tomato"* is in a complete state (left picture), GLIP (which is a well-known language-image model pretrained with large-scale multimodal data) can correctly detect the visual region with a high confidence score. However, as the state of target object *"tomato"* changes (i.e., *"tomato"* is cut into slices in the right picture), GLIP detects the visual region of *"tomato"* with a low confidence score and even is prone to wrongly recognize it as another entity type (e.g., *persimmon*).

In our paper, we propose a sequence-aware grounded multimodal procedural entity recognition (SeqGMPER) method to detect both the textual procedural entities and the corresponding visual regions in images from multimodal procedural documents. Specifically, to capture the state changes of procedural entities as the procedure progresses, a Textual or Visual Sequential Feature Fusion (TSFF or VSFF) module is designed. The state features of textual or visual entities in current step take into account to that in the previous steps. Furthermore, to conduct the evaluation on GMPER task, we construct a new dataset, called *Wiki-GMPER* based on the WikiHow resource (Anthonio et al., 2020), in which we manually annotate the textural procedural entities and the corresponding bounding boxes in images.

To summarize, the main contributions of this paper are listed as follows:

- We explore a new problem named Grounded Multimodal Procedural Entity Recognition (GMPER), aiming to automatically recognize textual procedural entities and link the corresponding visual regions in images from multimodal procedural documents.

- We design a textual and visual sequential feature fusion method to capture the state changes of entities as the sequence or procedure progresses, which effectively assist the detection of both textual and visual entities from multimodal procedural documents.

- We create a new grounded multimodal procedural entity recognition dataset *Wiki-GMPER* based on the multimodal procedural documents. Extensive experiments are conducted on the Wiki-GMPER dataset to evaluate the effectiveness of our model in automatically detecting procedural textual and visual entities.

2. Related Work

One kind of important commonsense knowledge in our daily life is the instructions or procedures which are the form of a sequence of actions to complete the particular goals. Current well-known knowledge bases such as *Wiki-Data* (Vrandečić and Krötzsch, 2014), *Wikipedia* (Lehmann et al., 2015), *Freebase* (Bollacker et al., 2007) and *ConceptNet* (Speer et al., 2017) mainly focus on modeling *descriptive knowledge* (i.e., the attributions or features of things (Yang and Nyberg, 2015; Yuan et al., 2023)), but neglect another commonsense knowledge—*Procedural Knowledge* (i.e., the Knowledge of procedures or sequence of actions to achieve the specific goals). To automatically extract the procedural knowledge, existing work (Jermsurawong and Habash, 2015; Feng et al., 2018; Mysore et al., 2019; Qian et al., 2020; Yamakata et al., 2020; Anthonio et al., 2020; Jiang et al., 2020; Pal et al., 2021; Fang et al., 2022; Ren et al., 2023) are designed to identify the procedural entities or their relations from the textual procedure documents (e.g., food recipes and crafting). However, procedural documents often generally appear in a multimodal manner. Therefore, another kind of related works (Pan et al., 2020; Xu et al., 2020) to construct the step-level or entity-level workflow from the multimodal procedural documents. Nevertheless, they only treat the visual features as additional clues but fail to identify the fine-grained entity groundings in images, which suffer from the entity ambiguity (Yu et al., 2023).

Currently, there are two kinds of related works: Multimodal Named Entity Recognition (MNER) and Grounded Multimodal Named Entity Recognition (GMNER). Specifically, MNER has recently attracted considerable attention on social media, aiming to recognize the named entity in text posts with the help of visual features as additional clues. Most of MNER methods (Moon et al., 2018; Lu et al., 2018; Zhang et al., 2018; Arshad et al., 2019; Yu et al., 2020; Zheng et al., 2020; Arshad et al., 2019; Chen et al., 2021, 2022; Wu et al., 2020; Zhang et al., 2021a; Wang et al., 2022b; Jia et al., 2023) mainly focus on the multimodal features alignment and fusion to recognize the textual entities. However, they only regard the visual features as significant clues for textual entity detection but neglect the correspondence between the entity groundings in images. To solve this problem, Yu et al. 2023 propose a grounded multimodal named entity recognition (GMNER) method to extract entity-type-region triples from multimodal media posts. Different from current MNER and GMNER methods, GMPER task focuses on the multimodal procedural documents with multiple steps and complex interactions (e.g., state changes) between procedural entities as the procedure progresses. Motivated by these, we explore a problem of grounded multimodal procedural entity recognition (GMPER), aiming to extract the procedural entity and the corresponding bounding box groundings in images. In our paper, a new dataset *Wiki-GMPER* is built based on the WikiHow dataset bases and we propose a Sequence-aware GMPER method to capture the interaction among steps. Extensive experiments are conducted to evaluate the effectiveness of our proposed model.

3. Model

In this section, the problem definition of GMPER task is firstly given and then we describe our proposed Sequence-aware Grounded Multimodal Procedural Entity Recognition model (SeqGMPER) in detail.

3.1. Problem Definition and Notations

Given a multimodal procedural document with a sequence of steps $D = \{s_1, s_2, \ldots, s_{L_d}\}$ and a corresponding sequence of images $V = \{v_1, v_2, \ldots, v_{L_d}\}$, the goal of the Grounded Multimodal Procedural Entity Recognition (GMPER) task is to extract a set of entity tuples:

$$Y = \{(e_1, r_1), \ldots, (e_t, r_t)\} \quad (1)$$

where L_d denotes the number of steps, s_i denotes the i-th step containing a sequence of words $s_i = \{w_{i,1}, w_{i,2}, \ldots w_{i,L_s}\}$ in a procedure document; The (e_i, r_i) refers to the i-th entity tuple, where e_i is the i-th procedural entity and r_i is the corresponding bounding box groundings in an image. Note that when the procedural entity e_i does not contain any visual region in an image, the visual region r_i is set as *None*. Meanwhile, the visual region r_i can be defined as a *4-D* vector $(r_i^{x_1}, r_i^{y_1}, r_i^{x_2}, r_i^{y_2})$ which refers the top-left and bottom-right positions of the grounded bounding box in the image, respectively.

3.2. Multimodal Feature Representation

3.2.1. Text & Image Representation

Inspired by the success of grounded language-image pretrained model GLIP (Li et al., 2022) (which pretrained with a large-scale multimodal data) in object detection and phrase grounding tasks, we employ the pretrained multimodal encoder in GLIP (Li et al., 2022) to extract features for both the text and image in each step. Given a procedural document D, Specifically, given one step in a procedural document D, which contains a sequence of words $s_i = \{w_{i1}, w_{i2}, \ldots, w_{iL_s}\}$ and the corresponding image v_i as the input fo the text encoder and visual encoder in GLIP respectively, the

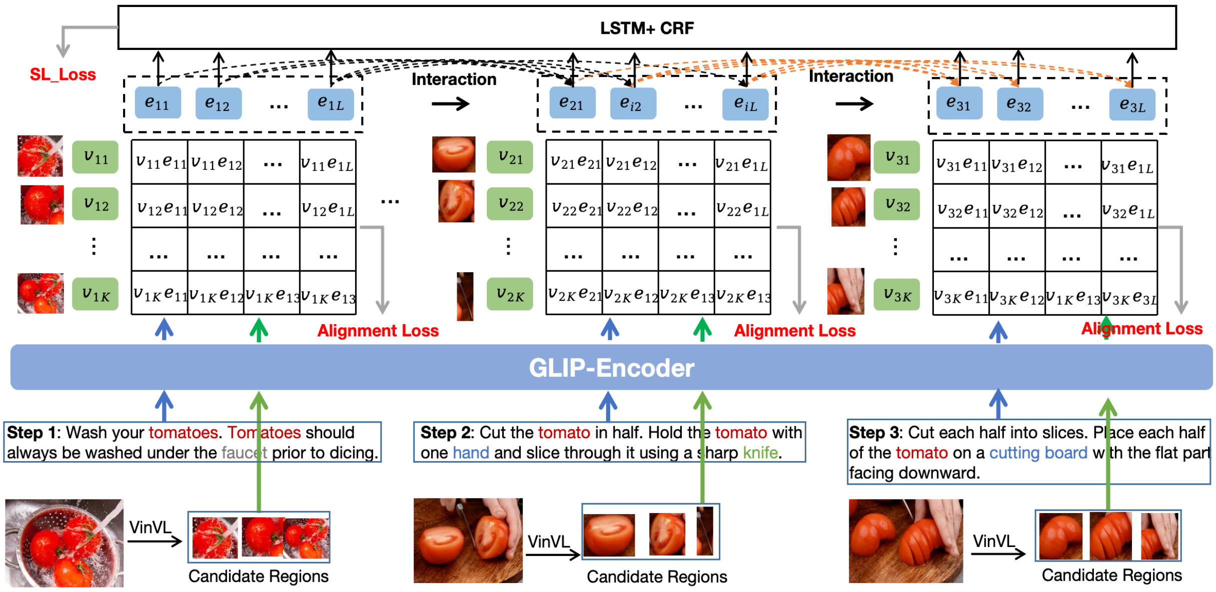


Figure 3: The Framework of Our Proposed Model SeqGMPER

word embedding matrix $\boldsymbol{S}_i = \{\boldsymbol{w}_{i1}, \boldsymbol{w}_{i2}, \ldots, \boldsymbol{w}_{iL_s}\}$ and the image feature map $\boldsymbol{M}_i$ can be obtained, where $\boldsymbol{S}_i \in \mathbb{R}^{L_s \times d_t}$, $\boldsymbol{w}_{ij} \in \mathbb{R}^{d_t}$, $\boldsymbol{M}_i \in \mathbb{R}^{d_v \times d_w \times d_h}$ and d_v denotes the number of the convolution kernel (i.e., the number of feature maps). Then, the mean-pooling operation for each feature map $\boldsymbol{M}_i$ is conducted and we can finally obtain the feature representation $\boldsymbol{v}_i$ for the i-th image, where $\boldsymbol{v}_i \in \mathbb{R}^{d_v}$.

3.2.2. Candidate Region Representation

Following Yu et al. (2023), a widely-adopted object detection model VinVL (Zhang et al., 2021b) is utilized to extract the candidate semantic visual region (i.e., the candidate bounding box groundings). Then, we rank candidate visual regions based on their detection probabilities. Specifically, for the i-th step in a multimodal procedure document, we identify the top-K candidate visual regions $C_i = \{c_{i1}, c_{i2}, \ldots, c_{iK}\}$, where the region c_{ij} can be denoted as a *4-D* vector $(c_{ij}^{x1}, c_{ij}^{y1}, c_{ij}^{x2}, c_{ij}^{y2})$ which respectively refers to the top-left and bottom-right positions of the candidate bounding box. Then, the feature map of each candidate visual region can be obtained by extracting the scaling feature area of the corresponding original image feature map $\boldsymbol{M}_i$. In the same way, the mean-pooling operation is used to obtain the final feature representation of the candidate visual regions $\boldsymbol{R}_i = \{\boldsymbol{r}_{i1}, \boldsymbol{r}_{i2}, \ldots, \boldsymbol{r}_{iK}\}$, where $\boldsymbol{r}_{ij} \in \mathbb{R}^{d_v}$.

3.3. Multimodal Sequential Feature Fusion

Since the steps of the multimodal procedural documents are interdependent and interrelated, the entities and regions discovered in the previous step can provide the important clues for the identification of entities and regions in the following steps. For example shown in Figure 1, we can observe that the token "*tomato*" would be regarded as a procedural entity with a high probability since the procedural entity "*tomato*" appears in previous step. Likewise, the identified visual region in current step would be also beneficial for the following steps' visual region detection. Motivated by this observation, we design a Multimodal Sequential Feature Fusion Module to capture the interactions between procedural entities and visual regions between steps. For the sequence data of different modalities (i.e., textual and visual modalities), we respectively conduct the sequential interaction feature fusion.

Sequential Element Attention Mechanism: For both textual sequence (i.e., word sequence in each step) and visual sequences (i.e., candidate visual region sequence in each step), we respectively adopt the sequential element attention mechanism to capture the interaction features among steps. For the convenience of description, we uniformly use $\boldsymbol{X} = \{\boldsymbol{T}_1, \boldsymbol{T}_2, \ldots, \boldsymbol{T}_n\}$ to represent the sequences in both textual and visual modalities, where $\boldsymbol{T}_i = \{\boldsymbol{t}_{i,1}, \boldsymbol{t}_{i,2}, \ldots, \boldsymbol{t}_{i,m}\}$ denotes the sequence of element feature representation and m denotes the length of sequence. Thus, given the previous step T_{i-1} and current step T_i, each fused element representation $\boldsymbol{t}_{i,j}^{fuse}$ can be calculated as follows:

$$\boldsymbol{t}_{i,j}^{fuse} = [\sum_{j=0}^{m} \alpha_{i-1,j} \boldsymbol{t}_{i-1,j}; \boldsymbol{t}_{i,j}] \quad (2)$$

where $\boldsymbol{t}_{i-1,j}$ denotes the feature representation of the j-th element in previous step T_{i-1}. The important degree $\alpha_{i-1,j}$ for the each sequential element t_{ij} in step T_i can be calculated as follows:

$$\alpha_{i-1,j} = \frac{e^{\boldsymbol{t}_{i-1,j}\boldsymbol{t}_{i,j}}}{\sum_{k=0}^{m} e^{\boldsymbol{t}_{i-1,k}\boldsymbol{t}_{i,j}}} \tag{3}$$

Textual Sequential Feature Fusion: For the textual modality, given a word sequence $\boldsymbol{W_i} = \{\boldsymbol{w}_{i,1}, \boldsymbol{w}_{i,2}, \ldots, \boldsymbol{w}_{i,L_s}\}$ in each step from the multimodal procedural document, the Sequential Element Attention can transfer them into another representation sequence $\boldsymbol{W_i^f} = \{\boldsymbol{w}^f_{i,1}, \boldsymbol{w}^f_{i,2}, \ldots, \boldsymbol{w}^f_{i,L_s}\}$. Thus, based on the sequential element attention module, given Each token representation in current step would fuse semantic features from previous step.

Visual Sequential Feature Fusion: Similar to the Textual Sequential Interaction Feature Fusion, given the the Top-K visual regions embeddings $\boldsymbol{R}_i = \{\boldsymbol{r}_{i1}, \boldsymbol{r}_{i2}, \ldots, \boldsymbol{r}_{iK}\}$ in the i-th step, the Sequential Element Attention is utilized to transfer them into another visual region representation sequence $\boldsymbol{R}_i^f = \{\boldsymbol{r}^f_{i,1}, \boldsymbol{r}^f_{i,2}, \ldots, \boldsymbol{r}^f_{i,K}\}$. Thus, based on the sequential element attention module, the visual region representation in current step would try to capture the similar visual regions in the previous step, which builds the feature interaction between steps.

3.4. Grounded Multimodal Procedural Entity Recognition (GMPER)

Based on Section *Multimodal Sequential Feature Fusion*, we can obtain the representation of token sequence and visual region sequence in each step. To conduct the GMPER task, three tasks i.e., Procedural Entity Recognition (PER), Binary Groundable Classification (BGC) and Grounded Procedural Entity (GPE) are conducted.

3.4.1. Procedural Entity Recognition

Given the multimodal procedural document (including the textual sequence and the visual region sequence), PER task aims to detect the procedural entities from token sequence in each step by understanding the language-visual features. Specifically, given the feature representation of token sequence in each step $\boldsymbol{W_i^f}$ (which obtained by section *Multimodal Sequential Feature Fusion*), we employ LSTM-CRF (Huang et al., 2015) layer to predict the corresponding sequence of labels $y_{per} = \{y_1, y_2, \ldots, y_{L_s}\}$,

$$p(y_{per}|w_{i,j}) = LSTM\text{-}CRF(\boldsymbol{W}_i^f) \tag{4}$$

where the label $y_i \in$ {B-Object, I-Object, O} and $w_{i,j}$ denotes the j-th token of the word sequence in the step s_i. Then, the CRF loss L_{entity} is adopted to optimize the model's parameters.

3.4.2. Binary Groundable Classification

Based on the procedural entities identified in PER, a binary classification task is employed to determine each predicted procedural entity is groundable or ungroundable. Specifically, considering multi-token procedural entities, the entity embeddings $\boldsymbol{E}_i^f = \{\boldsymbol{e}^f_{i,1}, \boldsymbol{e}^f_{i,2}, \ldots, \boldsymbol{e}^f_{i,L_e}\}$ are obtained by mean-pooling the feature representations of multiple token belonging to the same entity, where $\boldsymbol{e}_{ij} \in \mathbb{R}^{d_t}$ and L_e is the number of identified procedural entities. Finally, the probability of the groudable and ungroundable procedural entity can be calculated as follows:

$$p(y_{bgc}|e_{i,j}) = Softmax(\boldsymbol{W}\boldsymbol{e^f_{i,j}} + b) \tag{5}$$

where $y_{bgc} \in \{0, 1\}$ and $\boldsymbol{W} \in \mathbb{R}^{d_t \times 2}$ and b are the parameter fo the BGC classifer. Then, the cross-entropy loss $L_{groudable}$ is utilized to optimize the model's parameters.

3.4.3. Grounded Procedural Entity

For the i-th step, we employ a crossmodal attention module (Tsai et al., 2019) to fuse entity-level embeddings $\boldsymbol{E}_i^f$ and visual region embeddings $\boldsymbol{R}_i^f$. We then obtain the probability distribution over all the visual regions for each procedural entity denoted by z_i, as follows:

$$\boldsymbol{H}_i = Crossmodal\text{-}Attention(\boldsymbol{E}_i, \boldsymbol{R}_i) \tag{6}$$

$$\boldsymbol{Z}_i = Sigmoid(\boldsymbol{W}_G\boldsymbol{H}_i + \boldsymbol{B}) \tag{7}$$

where $\boldsymbol{H}_i \in \mathbb{R}^{L_g \times d_c}, \boldsymbol{W}_G \in \mathbb{R}^{d_c \times K}, \boldsymbol{B} \in \mathbb{R}^{1 \times K}, \boldsymbol{Z}_i \in \mathbb{R}^{L_g \times K}$ and L_g denotes the number of groundable entities. Specifically, we set a threshold for the GPE task, the visual region $\boldsymbol{r}_{i,j}$ belongs to the entity if the predcition probability greater than 0.5. Then, the BCE loss is used to optimize the parameters of the entity grounding recovery module as follows:

$$L_{grounding} = BCE(\boldsymbol{Z}_i, \boldsymbol{Y}_{gpe}) \tag{8}$$

where $\boldsymbol{Y}_{gpe} \in \mathbb{R}^{L_g \times K}$ denotes the matrix of the ground true labels.

Finally, in the training stage, the three losses (i.e. L_{entity} and $L_{groundable}$ and $L_{grounding}$) are simultaneously used to conduct the parameter optimization, as follows:

$$L = L_{entity} + L_{groundable} + L_{grounding} \tag{9}$$

Dataset Statistics	Train	Test	Validation
# Doc.	809	299	122
# Step	4794	1341	701
Avg Step of Doc.	5.90	5.00	5.75
# Entity	19869	5836	2738
# Groundable	11029	2854	1252
# Ungroundable	8840	2982	1486

Table 1: The statistics of our annotated dataset Wiki-GMPER

4. Experiment

We firstly introduce the construction of the new dataset *Wiki-GMPER* and then analyze the experimental results in detail.

4.1. Dataset Collection & Annotation

We collect the corpus from the benchmark sequence ordering dataset i.e. WikiHow (Anthonio et al., 2020; Wu et al., 2022) which provides a collection of human-created *how-to* articles about various topics (e.g., Crafts, Computers and Recipes). Two topics i.e., *Crafts* and *Recipes* are selected to build *Wiki-GMPER*, a dataset of multimodal procedural documents with the procedural entity taggings and the corresponding bounding box annotations in images, as shown in Figure 1. For the procedural entity taggings, three well-educated annotators are employed to make annotations by averaging the candidate procedural corpus with the BRAT tool[4]. Then, the bounding box annotation is conducted with the graphical image annotation tool *LabelImg* tool[5]. To ensure the quality of human-annotation, each annotator is required to give the confidence score for each annotated label. We weigh the confidence score of each annotator for the same label and the label with the highest score will be preserved.

Statistically, the final dataset contains 1230 multimodal procedural documents with 6836 steps. Each step consists of a text description and a corresponding image. We split the final annotated dataset into train, test and validation sets with 7:2:1 ratio. Table 1 depicts the detailed statistics of the annotated dataset *Wiki-GMPER*.

4.2. Experimental Settings

We conduct extensive experiments[6] on our annotated dataset *Wiki-GMPER*. Following Yu et al. 2023, the VinVL model (Zhang et al., 2021b) is used to obtain the top-K candidate visual regions. We utilize the grounded language-image pretrained model (GLIP) (Li et al., 2022) to extract the features representation of both text and images. Thus, the dimension of word representation is set as 768. In each optimization step during training, one multimodal procedural document (containing multiple steps) is used (i.e., the hyper-parameter batch size is set as 1). We use the AdamW optimizer for parameter tuning with the learning rate 2e-5. In our experimental evaluation, the precision, recall and F1 metrics are utilized to evaluate the models' performance, following Yu et al. 2023.

In our experiments, we conduct the comparative experiments with two groups of related works, including the *text-only* based methods (BiLSTM-CRF-None (Yu et al., 2023), BERT-None (Kenton and Toutanova, 2019), BERT-CRF-None (Yu et al., 2023) and BARTNER-VinVL-NONE (Yan et al., 2021)) and the *multimodal* based methods (i.e., UMT-RCNN-EVG (Yu et al., 2020), UMT-VinVL-EVG (Yu et al., 2020), UMGF-VinVL-EVG (Zhang et al., 2021a), ITA-VinVL-EV (Wang et al., 2022a), BARTNER-VinVL-EVG (Yu et al., 2023) and H-Index (Yu et al., 2023)).

4.3. Result Analysis

4.3.1. Comparison with Related Models

To demonstrate the effectiveness of our proposed model, we conduct the comparative experiments with current related works on our annotated dataset *Wiki-GMPER*, as shown in Table 2. As we can observe, our proposed model obtains the better performance respectively on Precision, Recall and F1 scores and achieves the state-of-the-art performance. Specifically, comparing with existing text-only NER methods (e.g., BiLSTM-CRF (Huang et al., 2015), BERT-None (Kenton and Toutanova, 2019) and BARTNER (Yan et al., 2021)), our proposed model (i.e., *SeqGMPER*) obtains the higher F1 score with a large margin. Comparing the experimental results between existing text-only methods and our proposed model SeqGMPER-None, we analyze that our proposed model can effectively perform alignment and fusion of text and visual modality data. The comparative experimental results can demonstrate that the visual features from images significantly improve the performance of procedural entity recognition.

Moreover, existing MNER and GMNER methods (i.e., UMT-RCNN-EVG, UMT-VinVL-EVG (Yu et al., 2020), UMGF-VinVL-EVG (Zhang et al., 2021a), ITA-VinVL-EVG (Wang et al., 2022a), BARTNER-VinVL-EVG, H-Index (Yu et al., 2023)) are adapted into GMPER tasks. Compared with them, our proposed model achieves better performances respec-

[4] http://brat.nlplab.org/index.html

[5] https://github.com/HumanSignal/labelImg

[6] The code and datasets are publicly available at https://github.com/betterAndTogether/SeqGMPNER

Model		Pre.	Rec.	F1
Text Only	BiLSTM-CRF-None	16.45	14.08	15.17
	BERT-None (Kenton and Toutanova, 2019)	19.96	20.53	20.24
	BERT-CRF-None	19.86	21.82	20.79
	BARTNER-None (Yan et al., 2021)	20.30	22.92	21.53
Text+Image	UMT-RCNN-EVG (Yu et al., 2020)	32.47	33.91	33.18
	UMT-VinVL-EVG (Yu et al., 2020)	38.14	39.82	38.96
	UMGF-VinVL-EVG (Zhang et al., 2021a)	37.70	39.89	38.76
	ITA-VinVL-EVG (Wang et al., 2022a)	38.85	40.76	39.78
	BARTNER-VinVL-EVG (Yu et al., 2023)	34.08	39.76	36.70
	H-Index (Yu et al., 2023)	41.45	43.37	42.38
	SeqGMPER-None (Ours)	40.20	40.86	40.53
	SeqGMPER (Ours)	**44.86**	**43.74**	**44.28**

Table 2: The Comparative Experimental Results with Current Related Methods. The model "{X}-None" denotes the region predictions default as *None* (i.e., Ungroundable).

Methods	Pre.	Rec.	F1
SeqGMPNER	**44.86**	**43.74**	**44.28**
SeqGMPNER w/o TSFF	44.30	41.06	42.62
SeqGMPNER w/o VSFF	43.82	40.98	42.35

Table 3: Ablation Experiments of Our Model

Tasks	Pre.	Rec.	F1
PER	78.77	83.26	80.96
BGC	69.71	81.97	75.35
GPE	64.00	59.49	61.66

Table 4: The average experimental results on three subtasks: Procedural Entity Recognition (PER), Binary Groundable Classification (BGC) and Grounded Procedural Entity (GPE).

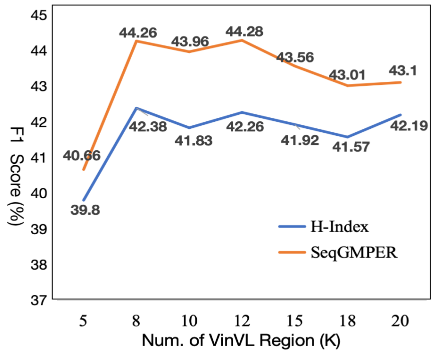
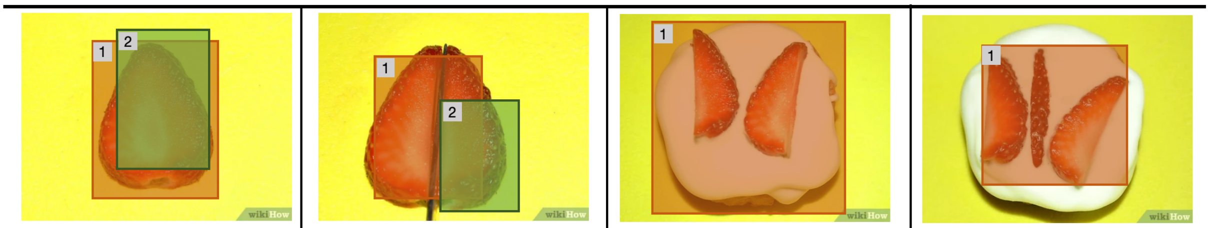


Figure 4: The impact of the value of K (Num. of the VinVL regions) on GMPER task for *H-Index* and our proposed model *SeqGMPER*.

tively on Precision, Recall and F1 scores, as shown in Table 2. We analyze that existing MNER or GMNER methods can only recognize the procedural entity and identify bounding box groundings for each step individually (i.e., including a text description and a corresponding image). Thus, they cannot capture the state changes of visual entities as the procedure progress, which impacts the detection of bounding box groundings. Instead, our proposed model with the sequential feature fusion module can build the connections between steps respectively for textual and visual feature representation. The comparative experimental results in Table 2 can demonstrate the effectiveness of our proposed model in capturing state changes in both textual and visual entities between steps.

4.3.2. Ablation Experiments

To further evaluate the effectiveness of each module in our proposed model, the ablation experiments are conducted. Specifically, we conduct the ablation experiments for the textual sequential feature fusion (TSFF) and visual sequential feature fusion (VSFF), as shown in Table 3. The performance of our proposed model drops significantly without the TSFF or the VSFF module, which can evaluate the effectiveness of our proposed TSFF and VSFF modules. Specifically, according to our observation, the procedural entities mentioned in current step would often appear in the later steps in a procedural document (e.g., the procedural entity "*tomato*" in Figure 1). Thus, the contextual steps would provide important clues for the procedural entity recognition in current step. The ablation experimental results can demonstrate that our proposed TSFF module can effectively capture the interaction among steps, which is beneficial to the procedural entity detection. In the same way, the state of visual entity would change as the procedure progresses. The ablation experimental results can evaluate that VSFF can effectively capture the state changes of visual entity to detect the bounding box groundings.



H-Index	Ours	H-Index	Ours	H-Index	Ours	H-Index	Ours
(strawberry, Box-2) ✓	(strawberry, Box-1) ✓	(strawberry, Box-2) ✗	(strawberry, Box-1) ✓	(cake, None) ✗	(cake, Box-1) ✓	(strawberry, None) ✗ (wings, None) ✓	(strawberry, Box-1) ✓ (wings, None) ✓

Figure 5: Prediction comparison on a multimodal procedural document "*How to Make Strawberry Butterflies*" between *H-Index* and our proposed model *SeqGMPER*. The symbols ✓ and ÃŮ denote correct and incorrect predictions.

4.3.3. Analysis of Sub-Tasks in GMPER

We also conduct the experiment to evaluate the performance of the three sub-tasks in our proposed model: Procedural Entity Recognition (PER), Binary Groundable Classification (BGC) and Grounded Procedural Entity (GPE). In training stage, all subtasks (i.e., PER, BGC and GPE) will be conducted to optimize the models' parameters. In order to independently evaluate our proposed model in BGC task, the ground-true labels of PER task are given to evaluate the performance in testing stage. In the same way, both the ground-true labels of PER and BGC tasks are given to predict the bounding box groundings in GPE task. As shown in Table 4, our proposed model can effectively recognize the textual procedural entities based on the multimodal semantic understanding. From the experimental results on BGC and GPE tasks, we can analyze that our proposed model can learn the multimodal language-image features and effectively detect the groundable procedural entities in images. To some extent, it can evaluate that our proposed model can effectively capture the interactions between steps.

4.3.4. Impact Analysis for Hyper-Parameter K

As shown in Figure 4, we also conduct the comparative experiments for our proposed model with different number of candidate VinVL regions. Compared with H-Index (Yu et al., 2023), our proposed model SeqGMPER obtains the better performance in all K-value settings. According to our observation, both our proposed model and H-Index obtain the lowest F1 score in GMPER task when the hyper-parameter K is set as 5. We analyze that most steps in procedural documents contain more than 5 visual entities in our annotated dataset. As the value of K increases, the performance of both H-Index and our proposed model improves significantly. They both achieve the highest F1 scores when the hyper-parameter K is set between 8 and 12, which can indicate that most of steps in our annotated dataset have around 8-12 visual regions. When the hyper-parameter K is set higher than 12, the performance gradually decreases.

4.3.5. Case Study

To intuitively explain the effectiveness of our proposed model, we conduct the case studies on GMPER task for H-Index (Yu et al., 2023) and our proposed model SeqGMPER. As shown in Figure 5, we can observe that both SeqGMPER and H-Index can correctly recognize the procedural entity "*strawberry*" in step 1. However, as the shape of "*strawberry*" changes in the following steps (i.e., step 2, 3 and 4), H-Index gradually fails to localize its bounding boxes. We analyze that existing works cannot effectively capture the interaction (e.g, the state changes of procedural entities) between steps. Instead, our proposed model SeqGMPER can correctly recognize both the procedural entities and their corresponding bounding boxes in images. The experimental results in this case study demonstrate that SeqGMPER can effectively capture the state changes of visual entities as the procedure progresses and achieve the better performance than H-Index.

5. Conclusion

In our paper, we explore a problem of automatically recognizing procedural entities in text descriptions and linking their corresponding bounding box groundings in images for multimodal procedural documents, named grounded procedural entity recognition (GMPER). Existing procedural knowledge extraction methods often focus on recognizing procedural entities or relations in text-only modal, but neglect a common multi-modal scenario. Existing related works i.e., MNER and GMNER cannot effectively capture the interaction between steps and suffer from the bounding box grounding prediction errors. To solve these problems, we propose a sequence-aware GMPER method to capture the state changes of procedural entity as the procedure progresses. Extensive experiments are conducted on our constructed dataset to evaluate the effectiveness of our proposed model.

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