

# A Cross-modality and Progressive Person Search System

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## ABSTRACT

This demonstration presents an instant and progressive cross-modality person search system, called “CMPS”. Through the system, users can instantly find the lost children or elderly persons by simply describing their appearance through speech. Unlike most existing person search applications which have to cost much time to find the probe images, CMPS will save more valuable time in the early stage of losing. The proposed CMPS is one of the first attempts towards instant and progressive person search leveraging the audio, text, and visual modalities together. In detail, the system first takes the speech that describes the appearance of a person as the input to obtain a textual description by speech-to-text conversion. Then the cross-modal search is performed by matching the textual embedding with the visual representations of images in the learned latent space. The searched images can be used as candidates for query expansion. If the candidates are not right, the user can quickly adjust their description through speech. Once a right image is found, the user can directly click it as a new query. Finally the system will give the complete track of the lost person by once-click. On the built CUHK-PEDES-AUDIOS dataset, the system can achieve 82.46% rank-1 accuracy in real-time speed. Our code of CMPS is available at <https://github.com/SheldongChen/Search-People-With-Audio>.

## CCS CONCEPTS

• **Computing methodologies** → **Computer vision**; • **Information systems** → **Similarity measures**.

## KEYWORDS

Person Search, Cross-modality Search, Progressive Search

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**Figure 1: The workflow of our cross-modality system.** 1) the system first takes the speech or text that describes the appearance of a person as the input; 2) the searched images can be used as candidates for query expansion of speech and text; 3) If the candidates are not right, the user can quickly adjust their query; 4) once right images are found, the user can directly click them as new query; 5) the system will give the complete track of the lost person by once-click.

## 1 INTRODUCTION

Person search or re-identification (Re-ID) is an important and challenging task in the multimedia and computer vision communities. With wide real-world applications such as intelligent video surveillance, smart retailing, etc. [17, 24], this task aims at searching for the same person captured by multiple non-overlapping cameras. It has achieved excellent results due to the deep learning-based model and large-scale labeled data [10, 17–21].

However, existing person search or Re-ID methods usually use images of a specific person as the probes [7, 14], which has limitations in real-world urgent scenarios. For example, when a mom lost her child in the mall, she knows what her child wears but cannot provide a photo. The time is very urgent in the early stage of losing. The fastest method is directly describing the child through speech or text description, then find more candidate images as query expansion. This is a common situation in real-life, while traditional Re-ID methods often neglect this situation [3, 6, 15, 22]. Although there have been some methods [4, 11, 12] for text-based person search in recent years, they only consider text as input. Speech is faster and more convenient than inputting text.

To this end, in this paper, we develop a simple, convenient, and real-time person search system of which the workflow is shown in Figure 1. This system has several featured properties: 1) It provides a convenient input and interaction mode, which takes the audio of speech as the input to search for a target person captured by cameras. By this means, users will not only interact with the system efficiently by speech instead of typewriting, but also provide

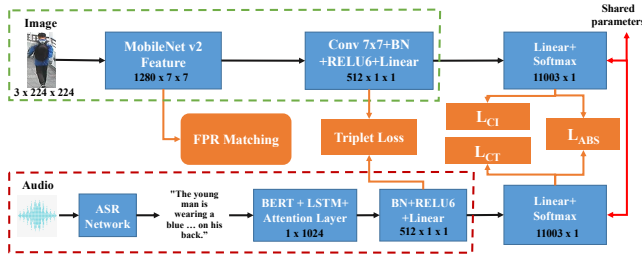


Figure 2: Architecture of the proposed network.

more fine-grained and detailed descriptions of the target person. 2) This system performs person search in a progressive manner to guarantee both the accuracy and speed, users can interactively input new queries and query expansion, which makes it able to find more accurate results with less time consumption[13].

## 2 METHODOLOGY

For solving this task, we design a new pseudo-siamese network which learns visual features and vocal features by two parallel subparts, as shown in Figure 2.

The first subpart is a Convolutional Neural Network (CNN), as shown in the green dotted box in Figure 2. We use MobileNet V2 [16] as the backbone of this subpart for extracting visual features due to its efficiency. After the feature part of MobileNet, we replace the pooling layer with the conv layer. To search persons with the image as the probe, we match images with the Foreground-aware Pyramid Reconstruction (FPR) [8], which can alleviate the mismatching caused by occlusion.

The second subpart adopts a Recurrent Neural Network (RNN), as shown in the red dotted box in Figure 2. We first use DeepSpeech2 [1] for speech recognition and use BERT [5] to get word embedding of the description. Then we feed the word embedding into Long Short-Term Memory [9] and the attention layer. Instead of softmax, we use sigmoid as a part of our attention layer, because it can solve the matching error better caused by sentences of different lengths.

Based on the above pseudo-siamese networks, we design a special loss function to optimize the whole network.

$$L = L_{CT} + L_{CI} + L_{ABS} + L_{triplet} + L_{FPR}. \quad (1)$$

$$L_{ABS} = E(\sum_i (P_T \cdot |P_T - P_I|) + \sum_i (P_I \cdot |P_I - P_T|)), \quad (2)$$

where  $L_{CT}$  and  $L_{CI}$  are the cross-entropy loss functions for images and text, respectively.  $L_{ABS}$  is used to balance the optimize of the RNN subpart and CNN subpart.  $P_T$  is ID label of text and  $P_I$  is ID label of images.  $L_{FPR}$  [8] is FPR matching loss and  $L_{triplet}$  [23] is triplet loss to learn the embedding space of speech and images.

## 3 THE SYSTEM AND EVALUATIONS

The interface of our system is shown in Figure 3. In our system, all models are trained on the CUHK-PEDES-AUDIOS dataset. In this dataset, we generate an audio file by Text-to-Speech for every text in CUHK-PEDES [12] and crop the images to 224×224.

Our model is trained on one TITAN RTX GPU for 100 epochs. The ASR network is fine-tuned on the CUHK-PEDES-AUDIOS dataset for 10 epochs. The experimental results are listed in table 1. In the dataset, each picture has several descriptive sentences, so when

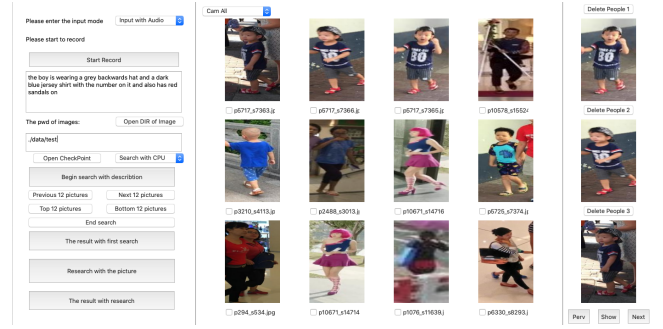


Figure 3: The interface of our cross-modal system. On the left of the interface is the input area, and when beginning a search, we can use different forms of input as probe. In the middle of the interface is the search result, and on the right is the candidate characters to show the tracks.

Table 1: The experimental results.

Method	Rank1	Rank10	mAP
deeper LSTM Q+norm [2]	17.19	57.82	-
GNA-RNN [12]	19.05	53.64	-
Latent Co-attention [11]	25.94	60.48	-
PWM-ATH [4]	27.14	61.02	-
CMPS-Audio-Fast*	35.03	70.14	34.61
CMPS-Audio	40.00	73.91	38.11
CMPS-Audio-Image**	82.46	95.93	76.12

\* CMPS-Audio-Fast uses Word2Vec as word embedding.

\*\* CMPS-Audio-Image uses image as probe.

calculating our Rank and mAP, we take the average value of this sentences. We referred to the previous papers and all the evaluation indicators. From the results, we can observe that our system outperforms existing real-time methods.

We quantitatively evaluate the operating speed of our system on TITAN RTX GPU. Due to the lightweight network structure, our network achieves excellent performance. Here we only compute the algorithm time without the human operation. As the used DeepSpeech2 can real-time recognize user's speech, we do not count it for search time. For the once CMPS-Audio-Fast search which uses the word embedding instead of Bert, the search speed is 10 ms per query. For the progressive CMPS-Audio-Image search with Bert, the search speed is 333 ms per query.

## 4 CONCLUSIONS

We propose an instant and progressive person search system through cross-modality retrieval. It can be used in the urgent situations where no probe image can be found. Users can directly find the target person with speed description in real-time. The system also supports the progressive search with searched images as query extension. In the future, we will further implement the system on more portable devices. We can also fuse more important information in the query, such as face image on the identification card.

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