

# LONG TERM LEARNING FOR IMAGE RETRIEVAL OVER NETWORKS

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## ABSTRACT

In this paper, we present a long term learning system for content based image retrieval over a network. Relevant feedback is used among different sessions to learn both the similarity function and the best routing for the searched category. Our system is based on mobile agents crawling the network in search of relevant images. An ant-behavior algorithm is used to learn the category dependent routing. With experiments on trecvid'05 key-frame dataset, we show that the smart association of category dependent routing and active learning leads to an improvement of the quality of the retrieval.

## 1. INTRODUCTION

Thanks to the generalization of multimedia devices (such as mobile phones, digital cameras, etc...), huge collections of digital images are available today. Content Based Image Retrieval (CBIR) has been successfully proposed to tackle the search in these ever growing collections [1]. The main idea is to build a description based on the images content, and to find similarities between descriptions [2]. Machine learning techniques have been successfully adapted to train a similarity function in interaction with the user (using her labeling of the results) leading to the so called "relevance feedback" [3, 4]. The best improvement has been done with the introduction of active learning, which aims at proposing for labeling the image that will at most enhance the similarity function when added to the training set [5].

With the expansion of networks such as the Internet, peer-to-peer networks or even personal networks, image retrieval has become a difficult task. As images are split into many collections over the web, the problem of CBIR is not only to find the most relevant images, but also to find the localization of relevant collections. Although CBIR in a distributed context has been noted as a interesting improvement [6], it has been, to our knowledge, the focus of few works. We have presented in a previous work [7] a system built for CBIR over networks. We carried out a smart cooperation between the interactive CBIR and a localization learning in a global architecture based on mobile agents.

However, all the labels gathered during the interaction are

forgotten at the end of the session of a classical CBIR system. One might think about re-using these labels for later session in order to benefit from the previous active learning [8]. In a single-user CBIR system, the resulting long-term learning is very slow due to the few labels available. However, in our distributed context, we can gather labels over sessions from many users. In that sense, the knowledge given to the system through the relevance feedback is huge. In this paper, we present a generalization for long-term optimization of our previous CBIR over networks system. The localizations of the categories are learned over several sessions, enabling a routing of the mobile agents specific to the searched concept. In the next section, an overview of our system is exposed. The sect. 3 contains the description of the routing learning algorithm during a session. Section 4 describes the long-term optimization. Finally, we present and discuss the experiments and results we obtained using our system on the trecvid2005 key-frame dataset<sup>1</sup> in sect. 5.

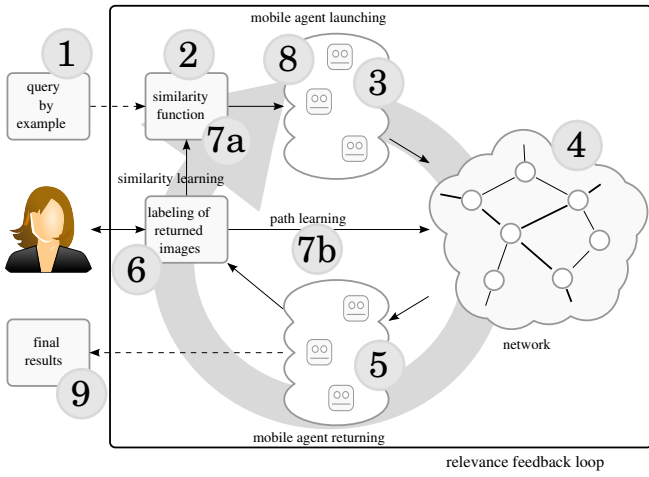
## 2. RETRIEVAL SCHEME

Our system is based on mobile agent technology. A mobile agent is an autonomous computer software with the ability to migrate from one computer to another and to continue its execution there. There are good reasons for using mobile agents in the distributed CBIR context, such as the reduction of the network load (the processing code of the agent being very small in comparison to the feature vector indexes) and the massive paralleling of the computation [9].

As described in Fig. 1, the user starts his query by giving an example or a set of examples to an interface (1). A similarity function based on these examples is built (2). Mobile agents are then launched with a copy of this similarity function (3). Every host of the network contains an agent platform in order to be able to receive and execute incoming mobile agents. The agent movements are influenced by markers (a numerical value locally stored on the host) following an ant-like behavior [10, 11], as described in section 3

On each platform, an agent indexing the local images is run, and retrieves the relevant images for the incoming agents.

<sup>1</sup>see <http://www-nlpir.nist.gov/projects/tv2005/>



**Fig. 1.** Functional description of our system showing the user in interaction with the relevance feedback loop (launching of agents, retrieval, display and labeling).

As soon as they receive the answer of the index agent, the mobile agents return to the user’s computer (5) and the results are displayed on the interface (6). The user can label these results (1: *relevant*, -1: *irrelevant*), and the similarity function is updated consequently (7a) as well as the good paths of the network (7b). As the similarity function we use is based on SVM analysis [12], the update only consists in adding the results and their labels to the training set and to train a new SVM.

Mobile agents are then relaunched with the improved similarity function. The interactive loop consists of several launching of mobile agents and labeling of the results (8). At the end of the interaction, mobile agents are launched for a very last time in order to retrieve the best results from each host (9). The number of retrieved images is proportional to the level of the markers leading to this host, assuring that most of the best retrieved images are provided by relevant hosts.

### 3. ROUTING LEARNING

During a session, the similarity function is learned as well as a routing of the agents leading them to host containing relevant images. This routing is done by the ant-like behavior of the agents. While moving from one host to another, agents are influenced by markers regarding the following rule :

$$P_i = \frac{ph_i}{\sum_{k \in S} ph_k} \quad (1)$$

Where  $P_i$  is the probability of an agent to move to host  $i$ ,  $ph_i$  being the value of marker of the host  $i$ , and  $S$  the possible destinations. In order to have the selected markers lead to the

hosts containing the images of the current category, we use an ant-like algorithm [13, 14] following the model of the ethologist J. L. Deneubourg [15] to reinforce the markers. Each time an agent moves towards a host, the selected marker is decreased as follows:

$$\Delta ph_i = -\alpha \cdot ph_i \quad (2)$$

And each time the user labels an image, the selected markers on the pathway taken by the agents to retrieve this image are increased:

$$\Delta ph_i = +\gamma \cdot u \quad (3)$$

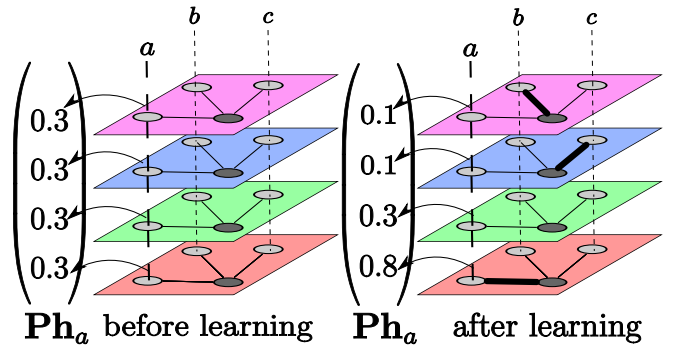
With  $u$  being 1 if the label is positive, 0 otherwise. Using this rules, the estimation of the marker  $ph_i$  is dependant on the estimation of  $\hat{u}$  the labels given by the user:

$$ph_i = \frac{\gamma \cdot \hat{u}}{\alpha} \quad (4)$$

Thus the higher levels of marker will be obtained for the hosts that gave the greatest number of positive labeling, leading to a routing associated with the session’s category.

### 4. LONG TERM MERGING OF SESSIONS

The main contribution of this paper is the generalization to long term optimization of all sessions. After several sessions, we dispose of several category related routings as explained in section 3. In order to re-use the routings in sessions concerning an already learned category, we put on each host  $i$  of the network several markers  $\{ph_{i,j}\}$ , each of them being related to a specific category.



**Fig. 2.** Evolution of the markers after long-term learning. At the very beginning, all three hosts  $a$ ,  $b$  and  $c$  have the same probability of being visited. After long-term learning some of the planes have specialized into one category.

The use of the markers  $\{ph_{i,j}\}$ ,  $j$  being fixed, for all host  $i$  of the network leads to a routing relevant for the associated category. Let us denote a *plane* such a routing (see Fig. 2). In order to benefit from these previously learned routing, we

build a function  $\psi$  selecting the markers  $\{ph_{i,j}\}$  corresponding to the searched category from  $\mathbf{Ph}_i$  the vector concatenating the  $ph_{i,j}$  available on the host  $i$ . The function  $\psi$  is obtained from a vector  $\Psi$  containing 1 for the relevant marker, and 0 otherwise :

$$\psi(\mathbf{Ph}_i) = \Psi^\top \cdot \mathbf{Ph}_i \quad (5)$$

As we do not have any *a priori* about the category being currently searched, we build the vector  $\Psi$  in interaction with the user. We associate to each set of markers  $j$  a probability  $W_j$  of being related to the current category. We sample a random vector  $\mathbf{X} = \{x_j\}$  of dimension  $N$  the number of set of markers with a uniform distribution over all dimension. The probabilities  $W_j$  are used as weights for  $\mathbf{X}$ , and  $\Psi$  is obtained as the projection on the max of the weighted  $x_j$ :

$$\Psi = \{\delta_{j,m}\}_{1 \leq j \leq N} \quad , \quad m = \underset{j}{\operatorname{argmax}}(\{W_j \cdot x_j\}) \quad (6)$$

Each time the user labels an image, the  $W_j$  corresponding to the markers that have been used to retrieve this image evolves regarding the following rule:

$$W_j \leftarrow W_j + \varepsilon(y - W_j) \quad (7)$$

Where  $y = 1$  if the label is positive, 0 otherwise. Thus, markers that gave a lot of positive labels will have a higher weight, which means a higher chance of being selected.

A  $\Psi$  is generated with a new random  $\mathbf{X}$  each time an agent is launched, assuring that all the dimensions will be explored until the weights converge to the dimension routing to the host containing the current category.

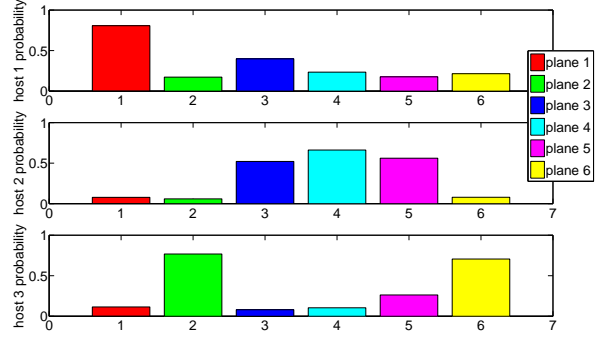
As both the function  $\psi$  and the markers level are learned at the same time (using the same reinforcement given by the user), the dynamics of the markers evolution should be slower than the one of  $\psi$ . Consequently, a set of marker is chosen (by convergence of the weights) before the markers are evolved.

## 5. EXPERIMENTS

We used the trecvid2005 key-frame dataset to test the influence of our category dependent routing on the retrieval. We put the three categories we tested (namely *airplane*, *explosion-fire* and *maps*) on three different hosts, and added about 4000 randomly chosen images from the category *entertainment* to each host (simulating the various content a real host contains). These were the possible destinations of our mobile agents. We ran one hundred of retrieval sessions which consist of launching of agents and displaying of results until 100 labels were obtained. At any session, the searched category was randomly chosen within the three hosted categories.

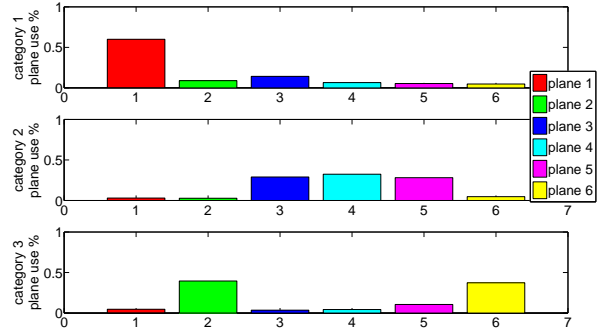
As shown on Fig. 3, each host had some of the markers specializing towards it. For instance, the third host has been

routed by the second and last planes, which means that a function  $\psi$  choosing one of these two planes will lead the agents to host 3.



**Fig. 3.** Relative values of each marker on the hosts. Each marker has specialized for one host.

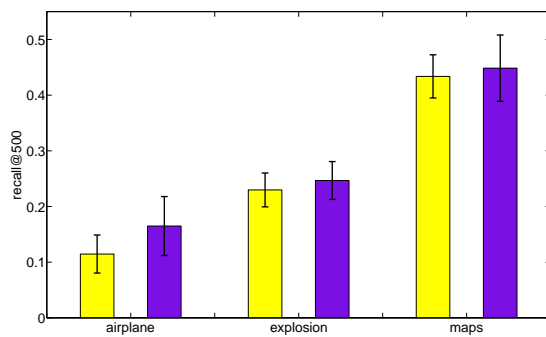
The markers that were used for each category are shown on Fig. 4. As we can see, all categories used a subset of the markers available, meaning that the markers did specialized for a category. We can clearly see the correlation between this specialization and the Fig. 3. The markers used for a session concerning a category where exactly those leading towards the host which contained it.



**Fig. 4.** Percentage of markers that were used for each category. Markers have been at most used for the category towards which destination they routed

In order to measure the improvement of using a category dependent routing, we ran one hundred retrieval sessions on a single host containing the images of all categories. This setup is called *centralized* there after. The *recall* for 500 images retrieved is shown on Fig. 5. As one can see, our system is better than the *centralized* setup by more than 3% in mean. For a difficult category like *airplane*, the gain is about 5%, whereas for an easy category like *explosion-fire*, the gain is about 2%. This improvement shows the improvement of taking in account the localization of relevant images into the

learning process.



**Fig. 5.**  $recall@500$  for the three tested categories. The distributed system performs better than the centralized one for all categories.

## 6. CONCLUSION

In this paper we have presented a CBIR system based on mobile agent technology with an ant-like behavior. The locations from where the images are retrieved depend on a set of markers. The association between these markers and categories is learning in interaction with the user, resulting into a category dependent routing. Our system carries out a smart cooperation between this routing and the active learning of the similarity function used for the retrieval, leading to an improvement of the recall.

While markers can be naturally shared between users, our system builds an user oriented semantic map of the network that can be used efficiently to improve the retrieval.

## 7. REFERENCES

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