The medGIFT Group in ImageCLEFmed 2013

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Abstract. This article presents the participation of the medGIFT group in ImageCLEFmed 2013. Since 2004, the group has participated in the medical image retrieval tasks of ImageCLEF each year. There are four types of tasks for ImageCLEFmed 2013: modality classification, image–based retrieval, case–based retrieval and a new task on compound figure separation. The medGIFT group participated in all four tasks. MedGIFT is developing a system named ParaDISE (Parallel Distributed Image Search Engine), which is the successor of GIFT (GNU Image Finding Tool). The alpha version of ParaDISE was used to run the experiments in the competition. The focus was on the use of multiple features in combinations with novel strategies, i.e, compound figure separation for modality classification or modality filtering for ad–hoc image and case–based retrieval.

1 Introduction

ImageCLEF [1] is the cross–language image retrieval track[1] of the Cross Language Evaluation Forum (CLEF). ImageCLEFmed has been focusing on medical image retrieval since 2004 [2–11]. In 2013, the medical task consisted of four subtasks including modality classification, compound figure separation, ad–hoc image–based retrieval and case–based retrieval [11]. A large database containing over 300,000 images from the biomedical literature was used for the tasks.

This article describes the participation of the medGIFT[2] research group in ImageCLEFmed 2013. The medGIFT group has participated in ImageCLEFmed since 2004 and is currently developing ParaDISE (Parallel Distributed Image Search Engine), which is the successor of GIFT[3] (GNU Image Finding Tool) that was used for many years as the baseline in ImageCLEF. As in 2012 [12], the alpha version of ParaDISE was used to run the experiments. In 2013, there are four main novelties in the submitted runs:

– a combination of multiple visual features was used;
– semantic information was included;

[1] http://www.imageclef.org/
[2] http://medgift.hevs.ch/
[3] http://www.gnu.org/software/gift/

– modality filtering was used for image– and case–based retrieval;
– compound figure detection was performed.

A combination of these strategies was used for the run submissions. For the modality classification task, the best medGIFT submission achieved a classification accuracy of 69.63% and was ranked in the fourth position. In its first year, the compound figure separation task only attracted three groups. MedGIFT achieved the best results, which could be expected since the data had been used by the group and the ground truth was created ahead of time. In the ad–hod image and case–based retrieval, the medGIFT group was ranked second for the visual and mixed submissions. The text runs submitted acquired average results with a simple Lucene baseline.

The rest of the paper is organized as following. In Section 2, the datasets and the techniques used are described. The runs submitted to the ImageCLEFmed 2013 benchmark are described and evaluated in Section 3. Finally, conclusions are presented in Section 4.

2 Datasets and Techniques

This section describes the basic techniques used in ImageCLEFmed 2013 by the medGIFT group. More detail on the setup of ImageCLEFmed 2013 can be found in [11].

Ten runs (three textual, three visual and four mixed) were submitted to the image–based retrieval task, five runs (one textual, three visual and one mixed) to the case–based retrieval task, ten runs (one textual, four visual and five mixed) to the modality classification task and two visual runs to the compound figure separation task.

2.1 Image Collection

The database provided for ImageCLEFmed 2013 [11] contains over 300,000 images of 75,000 articles of the biomedical open access literature. It is a subset of PubMed Central[4] containing over 1.5 million images. The distributed PubMed subset contains only articles allowing redistribution.

2.2 Textual Techniques

For text retrieval, the Apache Lucene framework was used. The built–in text analyser class named EnglishAnalyzer was used to apply lowercasing, stopword removal and stemming in their standard settings. The full text and the captions were indexed separately as the text to use depends on the exact goal of the search.

For modality classification, a step was included where a classifier using the Radlex ontology described in [13] was used for semantic consistency checking of

[4] `http://www.ncbi.nlm.nih.gov/pmc/`

images classified as containing radiology modalities. A mistake prevented this from being used in the submitted runs. Post–submission experiments show that the inclusion of semantics can improve the results.

2.3 Visual Features

In 2012, the bag–of–visual–words (BoVW) features using local descriptors were a focus using the scale–invariant feature transform (SIFT) and the CIELab color descriptor (namely bag–of colors, BoC [12]. In 2013, a combination of multiple features was explored as this was a successfully used technique in 2012 [10]. The following descriptors were chosen:

- color and edge directivity descriptor (CEDD) [14];
- bag of visual words using SIFT (BoVW) [15];
- fuzzy color and texture histogram (FCTH) [16];
- bag of colors (BoC) [17];
- fuzzy color histogram (FCH) [18];
- HSV color histogram [19];
- color layout [20];
- Tamura texture [21];
- singular value decomposition (SVD) [22].

These features were extracted from the test set (see Table 1). Then, the fusion of the best features was performed to obtain a good feature set (see Table 2). Due to time and resource limitations not all the possible combinations were tested and only the features performing well alone were combined in a simple linear way.

Table 1. Classification accuracy of each selected feature over the test set

Feature	CEDD	BoVW	FCTH	BoC	FCH	HSV	Color Layout	Tamura	SVD
Accuracy (%)	51.75	50.62	49.28	49.25	47.50	44.63	44.01	43.26	41.20

2.4 Compound Figure Detector

As seen in the ImageCLEFmed 2012 data set [10], a large portion of images found in the biomedical literature are compound figures (figures consisting of several subfigures). It was therefore important for the modality classification task to be able to detect this modality as accurately as possible.

For this reason, the compound figure separation application detailed in [23] was run on all the images in the modality classification test set in order to separate them into compound and non–compound figures. This way, the goal was to only classify the single–plane images in the subsequent steps.

Table 2. Classification accuracy of multiple features combined over the test set

Feature	Accuracy(%)
CEDD+BoVW	55.92
CEDD+BoVW+FCTH	57.15
CEDD+BoVW+FCTH+BoC	58.45
CEDD+BoVW+FCTH+BoC+FCH	**60.16**
CEDD+BoVW+FCTH+BoC+FCH+HSV	58.86
CEDD+BoVW+FCTH+BoC+FCH+HSV+Col. Layout	57.42
CEDD+BoVW+FCTH+BoC+FCH+HSV+Col. Layout+Tamura	56.88
CEDD+BoVW+FCTH+BoC+FCH+HSV+Col. Layout+Tamura+SVD	58.80

2.5 Training Set Expansion

In the modality classification task some of the image categories were represented by only very few annotated examples. Therefore, a training set expansion strategy was applied. For this expansion the images in the training set were indexed using only the textual information provided by Lucene. All the training images were queried against the full 300,000 images of the ImageCLEFmed 2013 data set and the 10 highest ranked retrieved images of each query were added as training images into the class of the query image. Only the images belonging to the 'compound or multipane images' (COMP) class were not queried because this class is well represented.

3 Experimental Results

This section details the techniques that were used to produce the runs for ImageCLEFmed 2013 and then evaluates the runs.

3.1 Modality Classification Runs

This year, medGIFT submitted 10 runs using the techniques described in Section 2. Two baseline runs were submitted: a visual and a textual. The visual baseline uses the features described in Section 2.3. The textual baseline is described in Section 2.2. The remaining runs are a combination of the baselines, the compound figure detection (Section 2.4), and the training set expansion (Section 2.5). The run IDs correspond to:

- Run1–**medgift2013_mc_5f**: this run uses only visual information as a baseline.
- Run2–**medgift2013_mc_5f_separate**: this run first classifies the images as compound or non–compound (see Section 2.4). Then, the non–compound images are classified using only visual information.
- Run3–**medgift2013_mc_5f_exp_k8**: this run uses the same techniques as Run1 but over an expanded training set (see Section 2.5).

- Run4–**medgift2013_mc_5f_exp_separate_k21**: this run uses the same techniques as Run2 but over an expanded training set.
- Run5–**medgift2013_mc_text_k8**: the images are classified using the textual information from the captions including semantic information.
- Run6–**medgift2013_mc_mixed_k8**: this run uses visual and textual information combined.
- Run7–**medgift2013_mc_mixed_exp_k21**: this run uses the same techniques as Run6 but over an expanded training set.
- Run8–**mc_mixed_sem_k8**: this run uses the same techniques as Run6 including semantic information (see Section 2.2).
- Run9–**medgift2013_mc_mixed_exp_sem_k21**: for this run visual and textual features are extracted as well as the semantic information. An expanded training set is used.
- Run10–**medgift2013_mc_mixed_exp_sep_sem_k21**: for this run the images are first classified as compound or non–compound. Secondly, the non–compound images are as in Run9.

3.2 Compound Figure Separation Runs

This year marked the introduction of a new subtask in ImageCLEF, the separation of compound figures. MedGIFT submitted two compound figure separation runs. Run11 simply serves as a point of reference, since it was also used in [23] and thus has an advantage over other techniques. Run12 uses a different method, which is not strictly designed for figure separation but provides a point of comparison. The run used a region detection algorithm mainly focused on volumetric medical image retrieval described in more detail in [24].

- Run11–**..._HESSO_CFS**: this run uses the MATLAB figure separation script mentioned above, which was also used as a first step in the manual generation of the ground truth.
- Run12–**..._HESSO_..._SCALE50_STANDARD**: run that uses a bidimensional version of the region detector mentioned above, at a scale of 50 pixels.

3.3 Image–based Retrieval Runs

This year the effect of modality filtering on the retrieval quality was investigated. For this purpose, the full image dataset was classified using the method of the best mixed run of the 2012 modality classification task [12]. The query images of each topic were also classified and a set of query modalities was produced. Images among the 1,000 top images retrieved by the retrieval methods that were classified into one of these modalities were placed in top of the other retrieved images.

Three approaches of modality filtering were tested. In the first one named "exact" only the modality detected by the KNN classifier for each query image of the topic was put into the query modality set. The second named "close" puts all the modalities detected by the KNN classifier of any query image into the topic. The third one named "prefix", is similar to the first but the broadest modality (diagnostic, general, compound) was used instead of the exact modality for boosting the image score in the retrieved set. Due to the limited number of submissions the "exact" approach was not submitted as it had a low performance in preliminary tests on the ImageCLEF 2012 collection.

Multiple features were used for visually indexing the dataset (see Section 2.3). Apart from the features used last year (SIFT–based BoVW and BoC features), more features were added for the image retrieval task. The CEDD and FCTH descriptors were also used, due to their good performance on ImageCLEF 2012 challenge. BoVW and BoC features that contain spatial information were used. For BoVW a spatial pyramid matching (SPM) approach was used [25] while an $n \times n$ spatial grid was used for BoC. The chosen pyramid depth level was $L = 1$ and the grid size was selected to be $n = 3$, after tuning on the ImageCLEF 2012 benchmark.

For the text runs, a late fusion of full text search with caption search was followed. Moreover, for each of these searches three different queries were fused for each topic. The first one queried the topic query for exact matching. The second connected the query terms with 'AND', while the third used 'OR' as a connector.

In the mixed runs, two different approaches were submitted. In the first approach, a linear weighted late fusion was used. The weights were tuned using the ImageCLEF 2012 benchmark. The second one used a late fusion (combMNZ) of the visual and text runs to rerank the images in the result set that was retrieved by the text run, similar to [26]. Preliminary experiments had shown that weighted fusion had the best performance among all other fusion rules and for this reason it was chosen for the comparison with the reranking runs. Below the characteristics of each of the 10 runs submitted are presented:

– Run13–**medgift_visual_nofilter**: visual run that uses the 6 features (BoVW, BoC, SPM_BoVW, Grid_BoC, CEDD and FCTH) and combMNZ fusion. No modality filtering is used.
– Run14–**medgift_visual_close**: same as Run13 but the "close" modality filtering approach is used.
– Run15–**medgift_visual_prefix**: same as Run13 but the "prefix" modality filtering approach is used.
– Run16–**medgift_text_nofilter**: text run using caption and fulltext search with combMNZ fusion. No modality filtering is used.
– Run17–**medgift_text_close**: same as Run16 but the "close" modality filtering approach is used.
– Run18–**medgift_text_prefix**: same as Run16 but the "prefix" modality filtering approach is used.
– Run19–**medgift_mixed_rerank_nofilter**: mixed run fusing the methods used in Run13 and Run16 to rerank the top 1,000 results of Run16. No modality filtering is used.
– Run20–**medgift_mixed_rerank_close**: same as Run19 but the "close" modality filtering approach is used.

– Run21–**medgift_mixed_rerank_prefix**: same as Run19 but the "prefix" modality filtering approach is used.
– Run22–**medgift_mixed_weighted_nofilter**: mixed run using linear weighted fusion for Run13 and Run16. Weights were set to be forvisual: 0.2, text: 0.8. No modality filtering is used.

3.4 Case–based Retrieval Runs

For the case–based retrieval task, similar techniques to the ones in Image–based retrieval task were submitted. For the mixed run, the visual features and the captions were used for retrieving a list of images that was then mapped to a list of associated articles. The new list was then fused with the article list returned by the baseline full text search. Below the characteristics of the 5 submitted runs are described:

– Run23–**medgift_visual_nofilter_casebased**: visual run that uses the 6 features (BoVW, BoC, SPM_BoVW, Grid_BoC, CEDD and FCTH) and combMNZ fusion. No modality filtering is used.
– Run24–**medgift_visual_close_casebased**: same as Run23 but the "close" modality filtering approach is used.
– Run25–**medgift_visual_prefix_casebased**: same as Run23 but the "prefix" modality filtering approach is used.
– Run26–**HES-SO-VS_FULLTEXT_LUCENE_ENGLISH**: baseline text run using full text search. No modality filtering is used.
– Run27–**medgift_mixed_nofilter_casebased**: mixed run using linear weighted fusion for Run23 and Run25. Weights were visual: 0.2, text: 0.8. No modality filtering is used.

3.5 Modality Classification Evaluation

This year medGIFT was the fourth group in the three types of run submissions. Table 3 shows the results achieved by the submitted runs. The baselines runs achieve the best results showing that the other techniques applied were not improving the accuracy. The use of multiple features indicate an improvement on the accuracy, achieving a better performance than last year's "easier" test data set. More work is necessary in the compound figure detection. In post–submission experiments it was found that the compound figure detection step did not achieve a better compound/non–compound separation accuracy ($\sim$ 70%) than the medGIFT baseline classifier ($\sim$ 79%). This caused a worse performance of the runs containing this step. Additionally, after the success of the expansion of the database in 2012, the results show that it is deteriorating the approach. Probably it is due to the fact that only textual information was used to expand the database. Finally, the semantic step did not modify the results due to the bug in the code.

Table 3. Modality classification results

Run ID	Run type	Accuracy(%)
Best ImageCLEF run	Visual	80.79
medgift2013_mc_5f	Visual	63.78
medgift2013_mc_5f_exp_separate_k21	Visual	61.03
medgift2013_mc_5f_separate	Visual	59.25
medgift2013_mc_5f_exp_k8	Visual	45.42
Best ImageCLEF run	Textual	64.17
medgift2013_mc_text_k8	Textual	62.04
Best ImageCLEF run	Mixed	81.68
medgift2013_mc_mixed_k8	Mixed	69.63
medgift2013_mc_mixed_sem_k8	Mixed	69.63
medgift2013_mc_mixed_exp_sep_sem_k21	Mixed	62.27
medgift2013_mc_mixed_exp_k21	Mixed	47.83
medgift2013_mc_mixed_exp_sem_k21	Mixed	47.83

3.6 Compound Figure Separation Evaluation

The two runs submitted by medGIFT were the best and the worst in the list, respectively, with only four runs being submitted. Table 4 shows the results achieved by the runs submitted by medGIFT. Predictably, the run that was used in previous work on the same data gave the best results, whereas the run using the 2D region detector, which is not optimized for compound figure separation, yielded mediocre results.

Table 4. Compound figure separation results

Run ID	Run type	Accuracy (%)
..._HESSO_CFS (Best ImageCLEF run)	Visual	84.64
..._HESSO_..._SCALE50_STANDARD	Visual	46.82

3.7 Ad–hoc Image Retrieval Evaluation

The results of the medGIFT runs are presented in Table 5. There are situations when "nofilter" or "close" filter perform better depending on the type of run (visual, textual or combined). Second best results were achieved in the visual runs using the baseline run ("nofilter"). On mixed techniques medGIFT was the second best group and on the textual runs medGIFT was the fourth group when using "close" filtering. In several queries the average precision was strongly improved by the modality filtering, while other queries had much lower performance, for example when the modality was not correctly detected. This indicates that more accurate modality classification should further improve retrieval performance. Results also show that the use of reranking in place of weighting for the fusion achieves better results. This is important for large–scale retrieval as visual search on the whole dataset is computationally costly. By having text retrieval as a first step, the image–based retrieval search subspace is significantly (magnitude of two orders) smaller.

Table 5. Ad–hoc image retrieval results

Run ID	Run type	MAP	GM–MAP	bpref	P10	P30
Best ImageCLEF run	Visual	0.0185	0.0005	0.0361	0.0629	0.0581
medgift_visual_nofilter	Visual	0.0133	0.0004	0.0256	0.0571	0.0448
medgift_visual_close	Visual	0.0132	0.0004	0.0256	0.0543	0.0438
medgift_visual_prefix	Visual	0.0129	0.0004	0.0253	0.06	0.0467
Best ImageCLEF run	Textual	0.3196	0.1018	0.2982	0.3886	0.2686
medgift_text_close	Textual	0.2478	0.0587	0.2513	0.3114	0.241
medgift_text_nofilter	Textual	0.2281	0.053	0.2269	0.2857	0.2133
medgift_text_prefix	Textual	0.2226	0.047	0.2235	0.2943	0.2305
Best ImageCLEF run	Mixed	0.3196	0.1018	0.2983	0.3886	0.2686
medgift_mixed_rerank_close	Mixed	0.2465	0.0567	0.2497	0.3229	0.2524
medgift_mixed_rerank_nofilter	Mixed	0.2375	0.0539	0.2307	0.2886	0.2238
medgift_mixed_weighted_nofilter	Mixed	0.2309	0.0567	0.2197	0.28	0.2181
medgift_mixed_rerank_prefix	Mixed	0.2271	0.047	0.2289	0.2886	0.2362

3.8 Case–based Retrieval Evaluation

In 2013, medGIFT submitted five runs in the case–retrieval task. The results are listed in Table 6. This year medGIFT obtained the second position in both visual and mixed runs. The results do not show significant differences with the use or without modality filtering.

4 Conclusions

This article describes the methods and results of the the medGIFT group for the ImageCLEF 2013 medical tasks. Ten runs were submitted each for the ad–hoc image retrieval and the modality classification tasks, five runs for the case–based retrieval task and two runs in the new compound figure separation task. In ImageCLEFmed 2013 medGIFT worked on runs based on multiple feature combinations. Several strategies were explored and not all techniques obtained improvements. Low results were obtained applying a database expansion strategy. This performance may be due to the use of only textual information for the indexing.

Table 6. Case–based retrieval results

Run ID	Run type	MAP	GM–MAP	bpref	P10	P30
Best ImageCLEF run	Visual	0.0281	0.0009	0.0335	0.0429	0.0238
medgift_visual_close_casebased	Visual	0.0029	0.0001	0.0036	0.0086	0.0076
medgift_visual_nofilter_casebased	Visual	0.0029	0.0001	0.0035	0.0086	0.0067
medgift_visual_prefix_casebased	Visual	0.0029	0.0001	0.0036	0.0086	0.0067
Best ImageCLEF run	Textual	0.2429	0.1163	0.2417	0.2657	0.1981
HES-SO-VS_FULLTEXT_LUCENE	Textual	0.1791	0.1107	0.1630	0.2143	0.1581
Best ImageCLEF run	Mixed	0.1608	0.0779	0.1426	0.18	0.1257
medgift_mixed_nofilter_casebased	Mixed	0.1467	0.0883	0.1318	0.1971	0.1457

Among the 2013 results, it is possible to observe that the compound figure separation is still a field to investigate in order to improve modality classification accuracy.

Future work of the medGIFT group aims at optimizing the use of the modality classification to help the retrieval. A correct incorporation of the semantic resources into the modality classification pipeline will be explored. MedGIFT also plan to further investigate the compound figure separation task.

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