Expansion of Queries and Databases for Improving the Retrieval Accuracy of Document Portions

An Application to a Camera-Pen System

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ABSTRACT

This paper presents a method of improving the accuracy of document image retrieval focusing on the application to a camera-pen system. In a camera-pen system, document image retrieval is employed for locating the pen-tip position on a page. A serious problem is that since the camera is mounted close to the pen-tip, the camera captures only a tiny portion of the page and the resultant image is under severe perspective distortion, resulting in lowering the retrieval accuracy. To solve this problem, we propose new geometrically invariant features as well as expansion techniques which increase the number of index features of either the database or the query images. From the experimental results, it has been found that the query expansion technique with features by combining affine and perspective invariants allows us the best performance that improves the accuracy of a baseline method more than 27%.

Categories and Subject Descriptors

I.7.5 [Document and Text Processing]: Document Capture—Document analysis

General Terms

Algorithms

1. INTRODUCTION

Document image retrieval is a process to retrieve document images based upon queries. The process can be classified into several categories according to types of queries. This paper concerns image queries obtained by cameras, or camera-based document image retrieval, which has the following important applications. (1) Retrieval of electronic documents: Printed documents are captured by a camera to find their electronic equivalents from the database. (2) Markerless augmented reality (AR): AR is to display various effects such as 2D videos and 3D animations onto the surface of a camera captured object. In general it is realized with the help of a special marker or tag called AR maker (tag), though it spoils the appearance of the object. Markerless AR is a technology to realize the same functionality without any markers [9]. For this purpose, it is necessary to know the location and orientation of a captured portion of the object only by analyzing the image itself. For the case of document image retrieval, it can be realized by detecting a captured portion of the page based only on the input image. Once the portion is identified any information can be superimposed onto the surface of the page. In other words, paper documents can be a new media. (3) Camera-pen: A camera-pen is an intelligent device that helps you record digital ink of what you write on physical paper. A famous example is the "Anoto pen" [1]. In this paper, we put a special focus on the application to camera-pens.

For making the above applications successful, it is necessary for retrieval methods to achieve the following properties: large-scale, efficient and accurate. Large-scale retrieval is necessary for making most of the applications meaningful. Both efficiency and accuracy become important properties especially if the database is large.

For the application of camera-pens, the most difficult problem is to achieve high accuracy since the quality of query images are considerably low as compared to those for other applications. For camera-pens, the camera is often mounted close to the pen-tip. This at least poses the following two problems: First, only limited regions can be captured as queries. Second, severe perspective distortions are unavoidable in query images. If the camera can capture only a limited region within the whole page, it is hard to identify which page of a document the camera captures, as well as where in the page it points. Severe perspective distortions make the problem of retrieval much harder since the appearance of the page is so different from its original upright document image in the database.

This paper proposes a solution to the above two problems

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by improving a method of document image retrieval called LLAH (locally likely arrangement hashing) [5]. The LLAH is a hash-based, real-time document image retrieval method. One of the characteristic points is its indexing scheme of document images, which is based on the two-dimensional distribution of feature points extracted from words and characters.

In order to solve the first problem, we introduce new features defined using geometric invariants on connected components. This allows us to improve the discrimination power of indexes. For the second problem, we propose a new method called "expansion". The origin of the second problem is that the query image is often far different from that in the database. Although the problem can be partly solved by using geometric invariants, it is not enough to solve the second problem. Another possible way is to transform the query and/or the database images geometrically closer with each other. This can be achieved by either (1) transforming the database images to be closer to the query image, or (2) transforming the query image to be closer to the database image. We call the first approach database expansion, and the second one query expansion. The second one is not called query normalization due to the following reason. It is generally hard to estimate accurately the perspective distortion of the query image. Thus we generate multiple queries from a camera-captured query image as possible upright images and use them as queries. In this paper we experimentally show which combination of invariants and expansion techniques is best suited to the application of camera-pens.

2. CAMERA-PEN SYSTEM

Before going into the details of the proposed improvements on LLAH, we briefly describe our intelligent camera-pen system starting from the motivation of its development.

The most famous camera-pen is undoubtedly the Anoto pen, which detects the pen-tip position globally by capturing arrangement of special fine dots on paper. Although it is portable and accurate, it has a serious drawback: it cannot be used without the special paper. The motivation of our research is to remove this limitation.

Our trial is twofold: One is to employ unevenness of paper surfaces to sense the pen-tip position [8]. It is, in some sense, similar to optical mice but can handle reappearance of a previously seen surface. A drawback of this method is that it is not so easy to know the global position on the document: it is currently capable of sensing the relative position within a sheet of paper. The other one is to use foreground pattern as a replacement of the Anoto dots [3]. With the help of a large-scale database that stores many pages of documents, it can sense on which document and where in the document the pen-tip is. A drawback of this latter method is that it cannot detect the position when the pen-tip is on the blank part of paper. Thus our final goal is to combine these two methods to replace the Anoto pen. This paper is to improve the accuracy of the latter method.

Figure 1 shows a prototype of the camera-pen. Although it is connected to a client computer using USB, it can be wireless if it is with a computing capability and memory. The process of tracking the pen-tip is illustrated in Fig. 2.

Figure 1: Camera-pen.

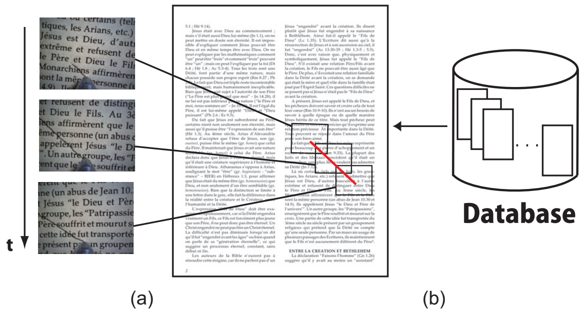


Figure 2: Tracking the pen-tip by retrieval.

Every frame of camera captured images is sent as a query image to the retrieval system for finding the document the pen is on from the database. As a side effect of the retrieval, it can be known where in the page the pen-tip is. By connecting the pen tip positions on the page, digital ink is recovered as its trajectory. Figure 3 shows the handwriting recovered by the prototype system. The scanned image is on the left of the figure, while the recovered digital ink is on the right. Although the strokes are partly jagged, it is capable of obtaining the digital ink successfully. Jags are due to instability of position estimation caused by motion blur, limited area of the captured part, severe tilts of the camera on the pen, etc., some of which will be solved by the improvements proposed in this paper.

3. DOCUMENT PORTION RETRIEVAL

As shown in Fig. 2, the role of retrieval for the application to camera-pens are not only for retrieving the page but also for locating captured portions within the page. In this sense, the task can be called "document portion retrieval". In this section, we describe the retrieval method called LLAH, and its problems when it is applied to camera-pen systems. We also describe a part of our proposed improvements, which is

Figure 3: Example of recovered digital ink.

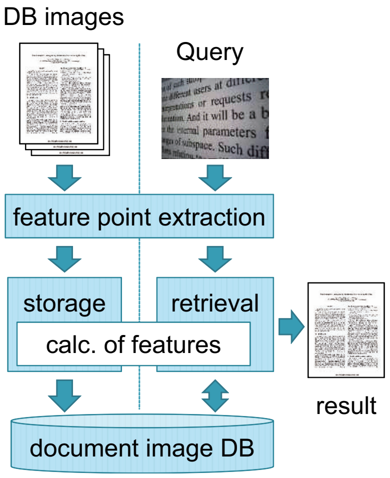


Figure 4: Document image retrieval.

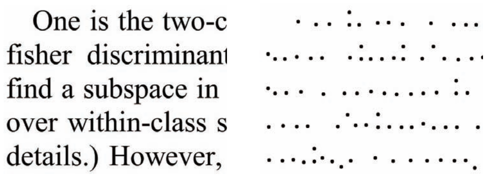


Figure 5: Feature point extraction.

by altering features for indexing.

3.1 LLAH

LLAH is a method of document image retrieval which takes as input camera-captured images of pages as queries. LLAH is unique in the sense that it enables us real-time retrieval. Figure 4 shows the overall processing of LLAH which is divided into two phases: database construction (left) and retrieval (right), both of which share processing steps of feature point extraction and calculation of features. The processing of database construction is as follows.

First, feature points are extracted from document images for the database. As feature points for camera-pen applications, we employ centroids of connected components as shown in Fig. 5.

Next, each feature point is indexed by using multi-dimensional feature vectors. Figure 6 illustrates an overview of the feature calculation. The feature vector represents two dimensional arrangement of surrounding feature points. Suppose we are now to calculate an index of the central red point (the point of interest). First we focus on the n points nearest from the point of interest. In the case for Fig. 6, $n = 7$. From these points, we use all possible combinations of m points out of n points, each of which corresponds to a feature vector for indexing. Thus the point of interest is indexed by $\binom{n}{m}$ feature vectors. Once the combination of m points is fixed, the feature vector is calculated by taking all possible combinations of four points out of m points. From each of four points combinations, an affine invariant is calculated as

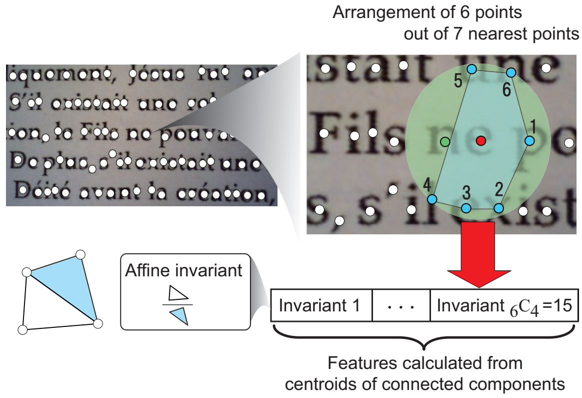


Figure 6: Basic features.

the area ratio of two triangles (see the lower left of Fig. 6.). For the case of $m = 6$, the number of combinations of four points is 15 so that we obtain a 15 dimensional real-valued feature vector. Finally the vector is quantized and stored in a hash table for fast access to the index. For more details, please refer to [5, 6]. In the following, the resultant features are called basic features.

3.2 Problems as a Method of Document Portion Retrieval

The above method of document image retrieval is effective for documents written in various languages [6]. For the application of camera-pen systems, however, there are at least the following two problems to be solved: (1) the limited captured region, and (2) the severe perspective distortion. Figure 7 illustrates the difference of queries that shows a reason of the problems. First problem is illustrated in Fig. 7. As compared to the query image in Fig. 7(a), the query image in Fig. 7 (b) covers a very limited area. In addition, the captured area of (b) is under a more severe perspective distortion as compared to (a). Since the number of textlines included in the captured image is so small, the number of basic features extracted from the image is also limited. This sometimes causes the failure of the retrieval. The second problem is as follows. It is not so easy to extract the same quantized features from severely distorted images, since the geometric distortion changes the area ratio.

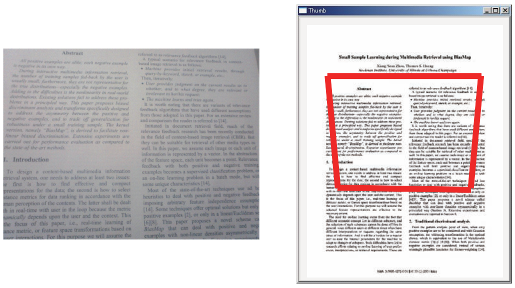
3.3 Improvement of Features

Our first attempt to solve the above problems is improvement of features as follows: (1) to employ not an affine invariant but a perspective invariant as the basic feature, (2) to improve the discrimination power of the feature vectors by adding a different feature to the quantized feature vectors. In the following, this added feature is called the additional feature.

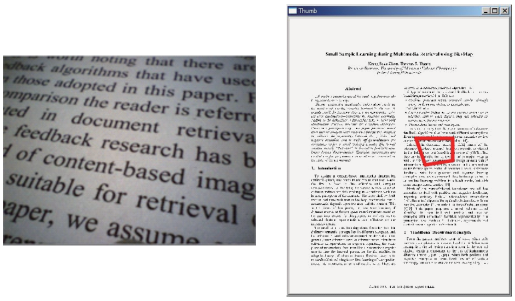
The first improvement is to use a cross ratio. Let A–E be 5 points around the point of interest. The cross ratio is defined as

$$\frac{P(A,B,C)P(A,D,E)}{P(A,B,D)P(A,C,E)} \tag{1}$$

where $P(x,y,z)$ is the area of triangle xyz [7]. Although it requires one more point as compared to the affine invariant,

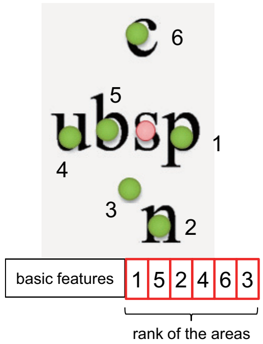


(a) document image retrieval

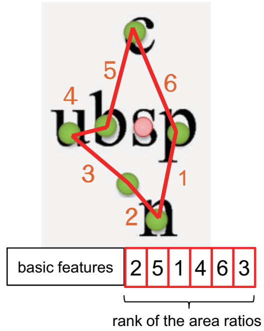


(b) document portion retrieval

Figure 7: Retrieval of document images and portions.



(a) rank of the areas



(b) rank of the area ratios

Figure 8: Additional features.

it is invariant to perspective distortion.

The second improvement is to employ the area of connected components. Figure 8 illustrates two additional features. Figure 8(a) represents the rank of areas of connected components. We utilize not values of areas but their rank in order to obtain robustness against different imaging conditions. Figure 8(b) is also the rank but the rank of area ratios. For example, 1 indicate the area ratio of the connected components of "p" and "n". Note that the rank of areas is an affine invariant and that of area ratios is a perspective invariant.

In the experiments described in Sect. 5, we evaluate combinations of the basic features and the additional features.

4. IMPROVEMENT BY EXPANSION

4.1 Limitation of Invariants

Although we have introduced various invariants for indexing, it is not enough to achieve high accuracy based only on them. This is because (1) affine invariants are fragile under severe perspective distortions, (2) perspective invariants are sensitive to imaging conditions and requires more feature points that are not always available.

These problems can be solved by having geometrically closer images. If the query image and its corresponding portion in a database image is geometrically close enough, matching these images becomes easier and more stable. Normalization is a way to make images similar. However, it is not an easy task to estimate correct normalization parameters. Another way is to generate some geometrically transformed images hoping that one of them is closer.

Generation of transformed images can be applied to either the database or the query. The former less affect retrieval speed, though it requires more memory to store features of generated images. The latter, on the other hand, needs only the same amount of memory, but makes the retrieval slower due to handling of generated multiple queries.

In this paper, we propose both methods: the former is called "database expansion" and the latter "query expansion" named after the commonly used processing of information retrieval [4].

4.2 Database Expansion

The process "database expansion" is to generate geometrically distorted images and store them into the database along with the upright original images. Figure 9 illustrates the process. Since unlimited application of image generation can easily blow up the required amount of memory, we sample the application areas. As shown on the left of Fig. 9, we define grid points by using X vertical and Y horizontal lines. We currently employ $X = 6$ and $Y = 10$ for A4 paper. Images whose centers are at grid points are cut and geometrically transformed in three different ways with the parameters of the elevation angle of 45° and the azimuth angles of -20°, 0° and 20°. Thus in total 180 image portions $(6 \times 10 \times 3)$ are added to the database.

4.3 Query Expansion

Another method we employ is query expansion which generates geometrically transformed images from the query image. While the purpose of database expansion is to make database images close to the query image, query expansion is to bring the query image close enough to the database image. In this sense, query expansion is an attempt to normalize query images. As previously described, however, it is not easy to estimate the correct parameters for normalization. Thus our method attempts to obtain near normalized images by the following three steps.

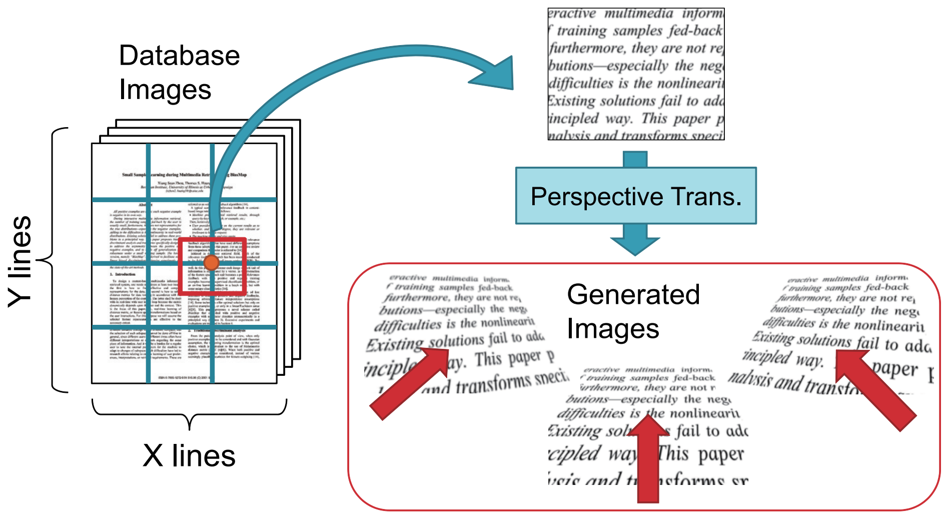


Figure 9: Database expansion.

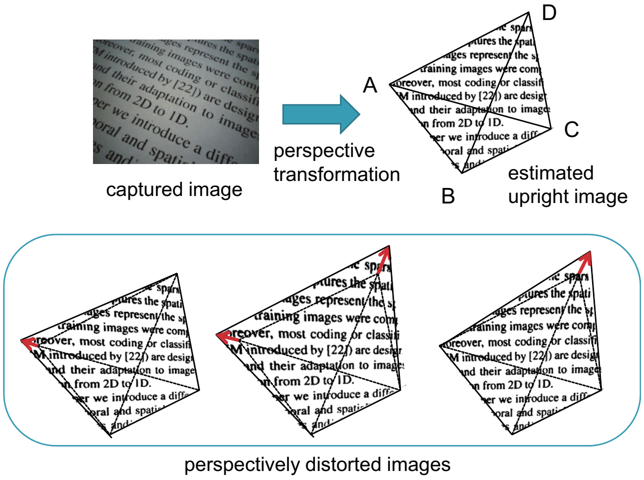


Figure 10: Query expansion.

The first step is to estimate the parameters of perspective transformation based on matching of the query image of the previous frame. This is done by using the RANSAC algorithm [2] with a set of matched feature points. As a result of the first step, we obtain an estimated upright image as shown in Fig. 10.

The second step is to apply perspective distortions aiming at obtaining more visually similar images for compensating estimation errors on the parameters of perspective transformation. Perspective distortions (perturbations) are applied by the method shown in the lower part of Fig. 10. The method deforms the image by extending one or both of diagonal lines with the rate α. As shown in this figure, we employ three different ways. New rectangles have diagonal lines with the length of both or either αAC and/or αBD, where AC and BD are the lengths of original diagonal lines.

The third step is to transform values of areas of connected components. A trivial way is to generate four images in

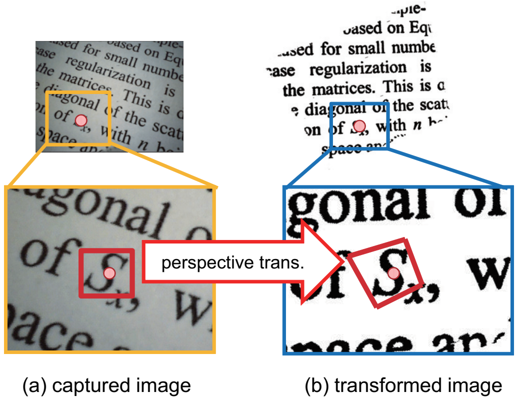


Figure 11: Transformation of the area of connected components.

Fig. 10: the estimated upright image, and its three perspectively distorted images. However, this process is too time consuming to keep the process of retrieval real-time. An important point to solve this problem is that we only need the information for calculating feature vectors. To be precise, information on the coordinates of feature points and that on the areas of connected components are necessary.

Once we know the parameters for perspective transformation, it is straightforward to obtain the transformed coordinates of feature points. Thus the problem to be solved here is how to obtain the areas of transformed connected components. To make the processing efficient enough, we employ an approximate way shown in Fig. 11. First, each connected component is represented as a circumscribing rectangle as shown in Fig. 11. Let S and R be areas of the connected component and the rectangle, respectively. Then in addition to the centroid, four corners of the rectangle are also transformed onto the new image shown in Fig. 11(b). The coordinates of the transformed rectangle allow us to calculate its area R'. The area of transformed connected components can be estimated as $S \cdot R'/R$.

Table 1: Methods for experiments. We have three types of methods: baseline methods (b1–b3), methods with database expansion (d1–d3), and methods with query expansion (q1–q3). Each type has three variants depending on basic and additional features employed in the method. Basic features are either the affine invariant (affine) or the perspective invariant (perspective). Additional features are one of the rank of areas (area) or that of area ratios (area ratio).

		features	
method	expansion	basic	additional
b1	w/o	affine	area
b2	w/o	affine	area ratio
b3	w/o	perspective	area ratio
d1	database	affine	area
d2	database	affine	area ratio
d3	database	perspective	area ratio
q1	query	affine	area
q2	query	affine	area ratio
q3	query	perspective	area ratio

By applying the above three steps to the query image, we obtain the expanded queries efficiently.

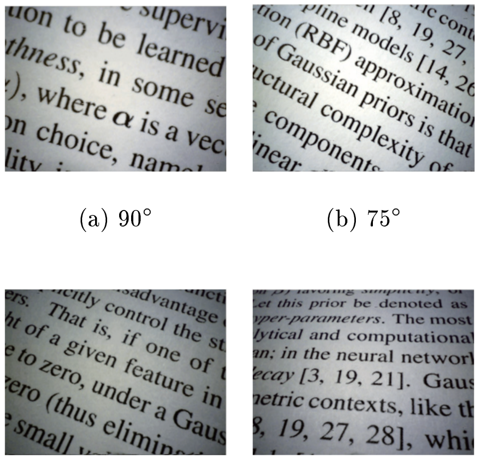
5. EXPERIMENTS

5.1 Conditions

The improvements proposed thus far were experimentally evaluated to determine what the best combination is among the proposed choices. Methods for evaluation are listed in Table 1. Parameters of LLAH used for the experiments were as follows. For the affine invariant as the basic feature, the values of n (no. of nearest points to look) and m (no. of points from which the feature vector is calculated; $m \leq n$) were set to $n = 7$ and $m = 6$. The number of dimensions of the basic features is $\binom{6}{4} = 15$. For the perspective invariant, $n = 8$ and $m = 7$ were employed since it needs one more point to calculate. The number of dimensions of the basic feature is $\binom{7}{5} = 21$.

The database for the experiments includes 1,000 pages of scientific papers with two columns layout printed on A4 paper. The size of database images was 5,100 × 6,600. We prepared a sequence of video frames that represents the trajectory of the pen-tip. We employed query images with four elevation angles: 90°, 75°, 60° and 45°, whose examples are shown in Fig. 12. The total number of frames was 300 for each elevation angle, from which the first 100 were used for setting up the value of parameter α for query expansion, and the rest (200 frames) were employed for evaluation of all methods. The size of query images was 640 × 480. For the database expansion, the size of portions cut at each grid point (see Fig. 9) was 960 × 720, which is 1.5 times as large as the query image.

We evaluated the retrieval results using the following criteria: (1) accuracy of document image retrieval, (2) that of document portion retrieval, (3) processing time, and (4) the amount of memory. Document image retrieval is correct if the ID of a document image is correctly retrieved. On the other hand, document portion retrieval is correct if the retrieved portion is correctly located on the page. It is determined visually by a human evaluator.



(a) 90° (b) 75° (c) 60° (d) 45°

Figure 12: Query images.

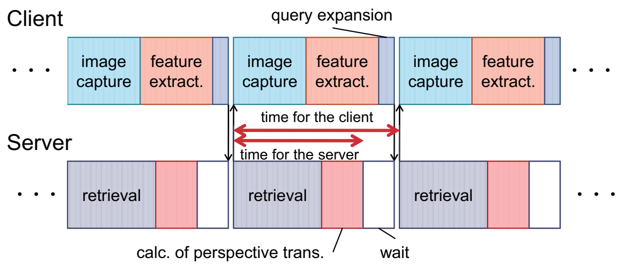


Figure 13: Time chart of the processing.

In order to evaluate the processing time, it is necessary to understand that the proposed method is based on the client-server model. Figure 13 illustrates the processes. At the client side, the processing time is divided into three parts: time for image capturing, feature extraction and query expansion if applied. At the server side, the time is divided into retrieval time and time for estimating the perspective transformation. After feature vectors are calculated at the client side (and expanded if necessary), and transferred to the server side for retrieval. Just after the transfer, the client can start processing of the next frame before receiving the result of retrieval for the current frame. This allows us to double the processing speed. It is often the case that the processing time at the server side is shorter than that at the client side. In such a case waiting time is introduced to meet the timing of the communication between the server and the client. We measured the time shown in Fig. 13 both on the client and the server sides excluding the waiting time.

We utilized the following computers in the experiments. The server was with an Opteron8378 2.4GHz CPU and 128GB memory, and the client was with a Athlon64 X2 3800+ 2.0GHz CPU and 2GB memory.

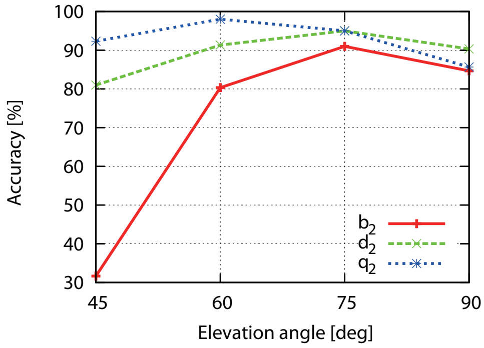


Figure 14: Accuracy of document image retrieval.

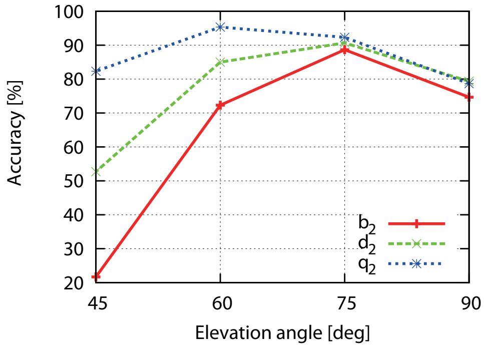


Figure 15: Accuracy of document portion retrieval.

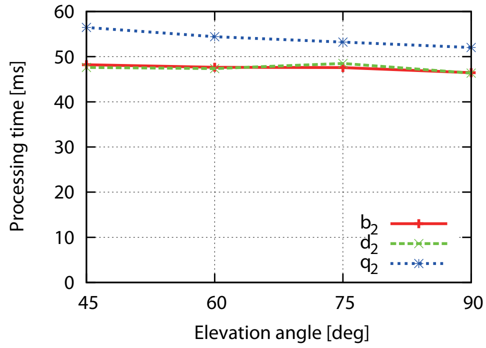


Figure 16: Processing time at the client side.

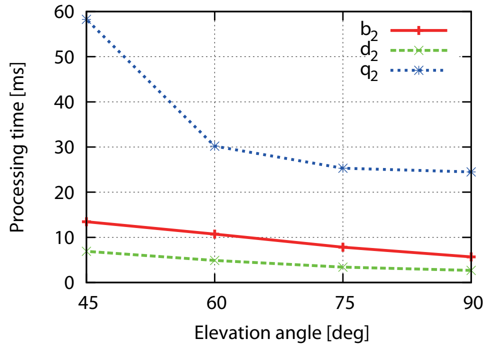


Figure 17: Processing time at the server side.

5.2 Results and Discussions

5.2.1 *Parameter setting*

First we set the parameter α for query expansion shown in Fig. 10 by measuring the accuracy of document image retrieval using 100 query images. The tested range was $0.8 \leq \alpha \leq 1.3$ with the increment of 0.1. For all variants of the query expansion method, $\alpha = 0.9$ or 1.2 performed well. The best performance for the methods q1, q2 and q3 was obtained with $\alpha = 0.9$, 1.2 and 0.9, respectively. In the following experiments, we utilize these values.

5.2.2 *Accuracy*

Table 2 lists the results of accuracy for document image retrieval as well as document portion retrieval. For each type of methods, i.e., baselines, database expansion and query expansion, the best performance was obtained by the variant 2, i.e., the affine invariant as the basic feature and the rank of area ratios as the additional feature. We picked out these three methods (b2, d2, q2) and plotted to the graphs shown in Figs. 14 and 15. From the table and these figures, it is clear that the query expansion outperforms other methods especially under severe perspective distortions. The second best is the method of database expansion. In other words, without expansion it is not easy to obtain good performance.

The following are some interesting points we found through the experiments.

- As features, the best selection is 2, i.e., the mixture of the affine invariant (as the basic feature) and the perspective invariant (as the additional features). The affine invariant basic feature is advantageous since it requires less feature points. This allows us to extract more features successfully from the same number of feature points. The rank of area ratios as the additional feature performs better since it is perspective invariants. Note that the rank needs the same number of feature points.
- For all methods the best performance was obtained not from query images with the elevation angle of 90°. When the angle is 90°, the captured portion is narrower as compared to other cases. This limits the number of extracted feature points, which resulted in lowering the accuracy. In other words, if a mechanism of dealing with perspective distortions is available, it is better for camera-pen systems to capture larger areas by mounting the camera at a slant position.

5.2.3 *Processing time*

Processing time at the client and server sides are shown in Figs. 16 and 17. At the client side, q2 needed longer time than other methods since it uses extra time for query expansion. At the server side, q2 also required the longest time since it utilized more feature vectors for querying. Another important point was that longer time is necessary for smaller elevation angles, since larger portions are covered within query images and thus more feature points are employed for retrieval.

For most cases, the processing time at the client side is longer than that at the server side except for the case of

Table 2: Accuracy of retrieval [%]. Underlines indicate the best performance for each elevation angle.

method	doc. image retrieval					doc. portion retrieval				
	45	60	75	90	ave.	45	60	75	90	ave.
b1	25.5	75.5	85.0	73.5	64.9	17.0	68.0	81.5	65.0	57.9
b2	33.5	81.0	88.5	83.0	71.5	25.0	77.0	86.0	71.0	64.8
b3	33.0	78.5	81.0	68.5	65.3	23.5	74.5	77.5	60.0	58.9
d1	68.5	88.0	89.5	80.0	81.5	48.5	79.5	80.0	66.5	68.6
d2	74.5	87.0	93.0	89.0	85.9	54.5	82.0	88.5	75.0	75.0
d3	57.0	86.5	89.0	80.0	78.1	47.5	83.5	81.5	65.5	69.5
q1	82.5	95.5	91.0	77.0	86.5	73.0	93.5	85.5	72.0	81.0
q2	92.5	97.5	94.0	83.5	91.9	82.5	95.0	91.0	76.5	86.3
q3	65.5	83.0	83.5	65.0	74.3	59.5	78.5	81.0	60.0	69.8

Table 3: Amount of used memory.

method	memory [GB]
b1, b2, q1, q2	3.2
b3, q3	3.9
d1, d2	10.8
d3	14.6

q2 with 45°. For q2 with 60° or more elevation angles, there is still room for improving the accuracy by using more expanded queries. For the angle 45°, however, the time at the server side is a bit longer than that at the client side, so that we cannot increase the number of expanded queries without slowing the whole processing.

5.2.4 Memory

As it can be easily estimated, the methods with database expansion needed the largest amount of memory as shown in Table 3. If we consider to apply the retrieval methods to larger databases, database expansion is disadvantageous since it needs much more memory space. The indexing method 3 (b3, d3, q3) used more memory as compared to other indexing methods (1 and 2), due to the higher dimensionality of feature vectors.

From all the above results of experiments, we can select the method q2, i.e., the method with the affine invariant and the rank of area ratios as indexing plus query expansion, is the best among the tested. It improved the accuracy of the baseline b1 27% or more for retrieval of both document images and portions.

6. CONCLUSION

We have proposed and evaluated new improvements of document image retrieval aiming at the application to camera-pen systems. The problems we attempt to solve in this paper is on query images, i.e., severe perspective distortions and small captured portions both of which are serious when the document image retrieval is applied to camera-pens.

The lessons we have learned from the experiments are (1) having more feature points is important to make the retrieval process stable, (2) compact indexing schemes using less number of feature points are also important, (3) the query expansion improves drastically the accuracy under the condition that the processing time is not a problem.

In order to complete our prototype camera-pen, we still have many problems including handling blank paper, motion blur and other imaging defects, which will be solved through future work.

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