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INDEXING AND RETRIEVING PHOTOGRAPHIC IMAGES USING A COMBINATION OF GEO-LOCATION AND CONTENT-BASED FEATURES

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Abstract. This paper presents a novel method that automatically indexes searches for relevant images using a combination of geo-coded information and content-based visual features. Photographic images are labeled with their corresponding GPS (Global Positioning System) coordinates and UTC time (Coordinated Universal Time) information at the moment of capture, which are then utilized to create spatial and temporal indexes for photograph retrieval. Assessing the performance in terms of average precision and F-score with real-world image collections revealed that the proposed approach significantly improved and enhanced the retrieval process compared to searches based on visual content alone. Combining content and context information thus offers a useful and meaningful new approach to searching and managing large image collections.

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1 INTRODUCTION

An image retrieval system enables users to browse, search and retrieve images from a large database of digital images [1]. Two approaches are commonly used, namely text-based image retrieval and content-based image retrieval (CBIR). The text-based approach requires images to be annotated with keywords that can then be easily searched, but this involves a vast amount of labor and personal subjectivity. A lack of clarity may also lead to mismatches in the retrieval process. The second approach, CBIR, indexes images in a database by identifying similarities based on visual features such as color, texture and shape [2, 3]. Typically CBIR system requires the construction of an *image descriptor*, which is formulated into a 2-tuple as (F_d, S_d), where $F_d : \{I\} \to R^n$ is a function that extracts a feature vector $\vec{f}$ from image I, and $S_d : R^n \times R^n \to R$ is a distance measure function that computes the similarity between two feature vectors corresponding to images in the database [4]. Although CBIR addresses the problems inherent in the text-based approach by automating the image description with feature extraction, it suffers from the problem of *semantic gap* [5]. This is the term used to describe the difficulty to infer semantic meaning from low-level feature analysis. Several approaches have been proposed to attempt to bridge the semantic gap using the following techniques:

1. classification systems,
2. inducing rational knowledge in the retrieval process,
3. utilizing the learning mechanism, or
4. making use of both visual content and textual information [6].

Inducing human knowledge is expected to result in satisfactory performances, as demonstrated in [7], but a time-consuming process that requires extensive training for the system, covering a wide range of situations. Consequently, this approach is best suited to highly restricted fields such as medical images. The learning mechanism has been proven to be very capable for learning and applying user knowledge, but it needs to store and process a large matrix of relevant information. Utilizing both content and textual information is a simple CBIR technique, but this type of textual information is not available in most other applications.

In the area of ubiquitous computing, many researchers have tried to use location information to provide a service in a timely fashion through location-aware technology [8]. This type of information is extremely useful in the representation of images and is one of the strongest memory cues when a user recalls past records [9]. The success of location-based techniques such as telematics raises an interesting question: can this technique also be used to improve search accuracy, given that location and time are two of the most important clues in the retrieval of photographs. Consequently, we extend our previous work [10] by creating spatial and temporal indexes in two separate layers to improve the performance of image retrieval systems and reduce the semantic gap based on the application of clustering techniques.

This paper is organized as follows: Section 2 reviews related works on image retrieval and location-aware techniques. Section 3 analyzes the key problems involved in developing a new method for producing an automatic index based on a location-stamp and time-stamp for each image, combined with content-based features. Section 4 describes a practical application of the new method, discusses the experimental results, and compares these to the results obtained using a search based on content analysis alone. Section 5 concludes by summarizing the findings and discussing the potential of this new approach.

2 RELATED WORK

This section summarizes recent researches into metadata-based models and the tools currently available for managing photographic image archives. The topic of GPS data handling for photo management has been extensively studied in the last few years. Toyama et al. [11] proposed the WWMX (World Wide Media eXchange) database, where large collections of images are indexed in terms of several pieces of metadata, including time and location information, while other researchers have applied a geo-life system that visualizes GPS data over digital maps and then analyzes historical events using the user's life pattern from raw GPS log data [12]. These approaches are primarily designed to manage images, and there is often a problem synchronizing geo-locations with images due to the separation between capturing device and management system. Similar issues hamper systems based on the use of manual annotations added when generating the metadata. For example, although the GeoTracker system allows users to aggregate, navigate and browse RSS-enabled content in digital maps [13], it does not support the creation of geo-referenced media. Qamra et al. [14] attempted to match landmark photos based on their photograph annotation and location context, while Kennedy et al. [15] employed a location-driven and tag-driven approach to representing, browsing and retrieving images using a Flickr dataset. These research studies all used manually pre-defined landmarks in their datasets. Tollmar et al. [16] presented a tool designed to help mobile users identify an unknown landmark by pointing at it with a camera phone and taking a photograph. Their IDeixis system first queries an image matching routine, and then searches the web using keywords associated with the user's location. These studies served as important precursors for the work reported here.

The new system developed in this study automatically creates a spatial and temporal index based on geo-location information and the date/time at which each image was created. This indexing information is embedded into the header of the image file, providing an efficient way to manage the data. Since a few high-end cameras can be interfaced to GPS devices, an input function of location tracking data acquired by GPS was utilized to solve the problem of synchronization, as described in Section 4.1.

3 PROPOSED METHOD

The main goal of this work was to evaluate whether the addition of spatial and temporal information can improve the image retrieval process. To achieve this goal, the proposed method utilizes GPS information and a time-stamp indicating where and when the photograph was taken. The resulting set of geographic location and date/time data are then used to automatically create two types of indexes for retrieval. The proposed system performs three major tasks, as illustrated in Figure 1.

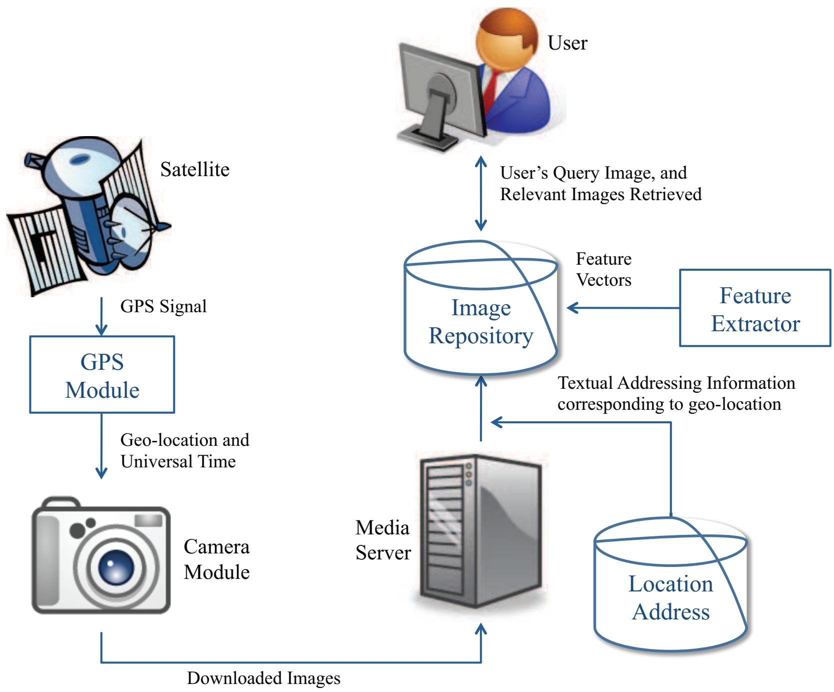


Fig. 1. Diagram of the proposed photographic image retrieval system

When the mobile device, equipped with a camera and a GPS module captures a picture, it immediately sends a request to the GPS receiver for the corresponding location information (i.e., latitude and longitude). The digital image and the coordinates are then compressed and saved, with the location information being stored in the image file header. The UTC time at which the image is captured is also automatically recorded. Textual information such as the place name and/or the name of the building at that latitude and longitude is imported as part of user's batch process when the image file is downloaded to the media server. In order to support the query-by-example process, several images relevant to the user's query image can be retrieved by searching for similar images. The next subsection presents the algorithm used to create the geo-spatial indexes, and assign all the photographic images to nodes.

3.1 Spatial and Temporal Indexes for Photo Clustering

An image that is associated and encoded with a geographical identifier is generally referred to as a geo-coded image [1]. Each geo-coded image can be classified into an appropriate subset based on these geographical coordinates. Figure 2 illustrates a sample set of photographic images and the corresponding track from GPS-derived location information.

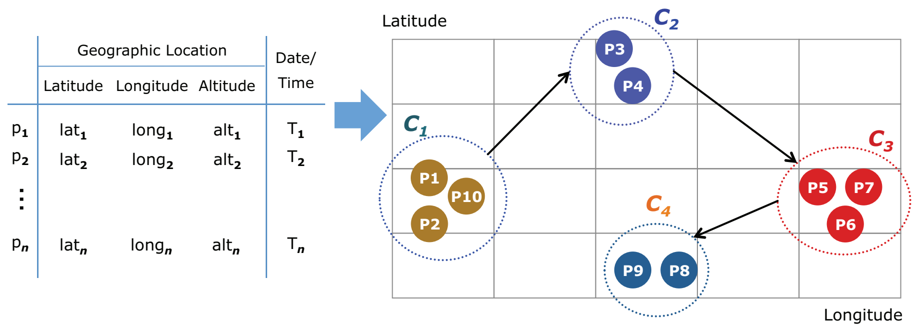


Fig. 2. Example of image clusters with time-sequence and corresponding location track. P_i denotes the temporal sequence of the photographs, and C_i indicates their classification in terms of their geo-location, represented by a dotted circle. Arrows represent the user's movements.

Let $P = \{p_1, p_2, \ldots, p_n\}$ represent a set of photographic images taken at certain times (from T_1 to T_n), displayed by ordering a time-series. and $C_i = \{p_i, p_{i+1}, \ldots, p_j\}$ represent a set of consecutive images taken in close proximity to each other corresponding to a location cluster whose members are included the set C. Note that non-sequential photos may be included in the same cluster: for example, p_1 and p_{10} are both included in C_1 in Figure 2. Once the photographs have been grouped into location clusters, an index (*the flat layer* in Figure 3) is automatically created for each image that incorporates the corresponding geo-location information. The index in the flat layer is built up of simple GPS coordinates and the time-stamp associated with each image, formulated with a tuple (*PhID*, *Lat*, *Long*, *UTime*). A photo ID

(PhID) is generated by the capturing device, the photograph's capture location is composed of latitude (Lat) and longitude (Long), and the capture time (UTime) representing universal time taken from the satellite.

An alternative index for spatial and temporal information (*the hierarchical layer*) is built with textual information obtained from the National Geospatial-Intelligence Agency (NGA), as shown in Figure 3. In order to create a geo-spatial index in the hierarchical layer, countries, provinces, counties and districts that correspond to the latitude/longitude are found in the addressing system. Since the spatial hierarchy may differ from the unified national addressing system, the system developed for this study uses a four-fixed hierarchy based on a geographic dataset of administrative regions. Thus, a photo entity can be formulated with a tuple (*PhID*, *HierIdx*, *LTime*) that contains a photo ID (PhID), 4-level hierarchies (HierIdx), and a local area time (LTime) computed from UTC. For example, a particular coordinate (i.e., N 37° 33′ 58″ and E 126° 58′ 51″) is considered to be in a country (*Korea*), a province (Seoul), a county (*Jongno-gu*), and a district (*Namdaemunro*). The user is then assumed to be located at a certain place at a certain time when the photograph is taken, in this case "*Seoul Jongno-gu, Aug. 15 2008*".

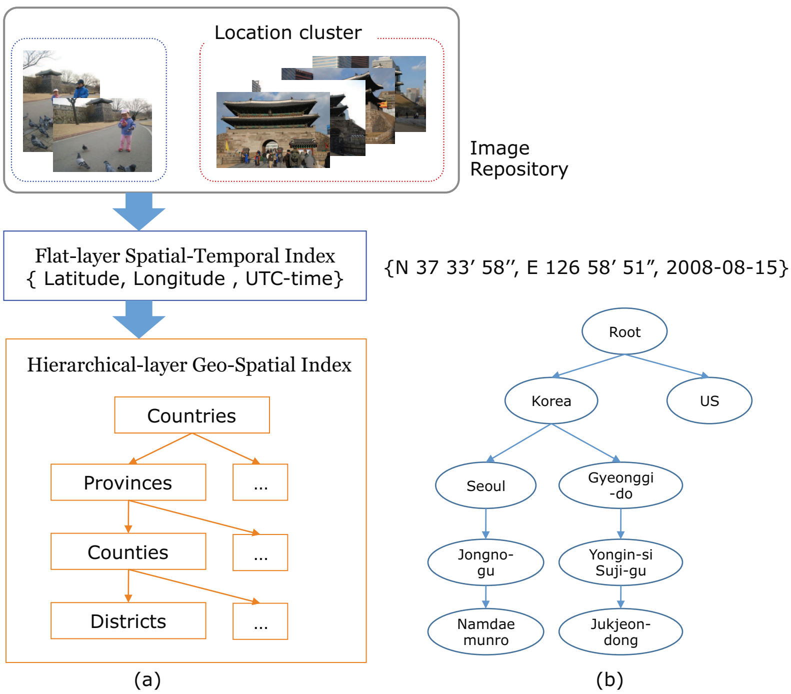


Fig. 3. The proposed index model a) Two-layer Geo-spatial Indexing, and b) an example of location hierarchy using textual information to illustrate place name clusters

For the query-by-example process, the proposed method adopts two different approaches to filter the relevant subset prior to content-based retrieval. In the first proposed approach, which is based on the use of the index contained in the flat layer, all images outside a certain distance and time interval from the query image are removed from the collection and the remaining images ranked in terms of the similarity of visual features. When this new descriptor is incorporated in each of the color and texture features described in the next subsection to simultaneously evaluate the performance of the image retrieval process, they are referred to as the Geo-location based color histogram (G-CH) and Geo-location based edge histogram descriptor (G-EHD), respectively. The relevant images filtered using this approach are defined by Equation (1).

$$\text{filtered subset} \in \{\forall I : D_{qt} \leq t \cdot \varepsilon \vee T_{qt} \leq (1-t) \cdot \mu\} \tag{1}$$

where I is the subset of images filtered, t is the user-defined criterion, and ε and μ are the user-defined boundary ranges for location and time, respectively. Setting $t = 0$ focuses solely on the spatial information, while setting $t = 1$ considers only the temporal information. D_{qt} is the distance between the query image and the target image computed with Equation (2), and T_{qt} is the gap between the times at which the two images were captured.

$$\begin{aligned} D_{qt} \quad = \quad & C \times \arccos[(\sin(lat_q) \times \sin(lat_t)) \\ & + (\cos(lat_q) \times \cos(lat_t) \times \cos(long_q - long_t))] \end{aligned} \tag{2}$$

where *lat* and *long* are the decimal degrees of latitude and longitude, and the indexes q and t represent the query and the target image, respectively. C is the constant used to convert the angle from radians to degrees.

In the other approach proposed here, which is based on the use of the index contained in the hierarchical layer, all images with the same node (included below) as the query image are selected and included in the ranking retrieval process. This new descriptor is once again incorporated on both features, this time as the hierarchical geo-location based color histogram (HG-CH) and hierarchical geo-location based edge histogram descriptor (HG-EHD). The selected subset is defined by Equation (3).

$$\text{selected subset} \in \{\forall I : \bigcup \sum_{j=i}^{m} [\exists_I | S_j]\}, \quad \text{where } j = i, i+1, \ldots, m \tag{3}$$

where m is the maximum number of hierarchical levels, and S_j is the subset of images belonging to the node of the j^{th} hierarchical level.

3.2 Visual Feature Extraction

Two image descriptors are used to extract the content-based visual features: a 64-bin color histogram (CH) and the well-known MPEG-7 edge histogram descriptor

(EHD) [17, 18]. CH provides a compact summarization of the color distribution by converting the color model, quantizing the colors in each image, and counting how frequently these colors occurs. EHD extracts information on the spatial distribution of edges in an image by dividing its gray-scale image into 4×4 non-overlapping blocks, and then categorizing the edge into 5 types (0°, 45°, 90°, 135° and non-directional). Using CH for each of two channels in Cb and Cr results in a 128-dimensional feature vector, while EHD yields an 80-dimensional feature vector.

Normalized histogram intersections for CH and EHD are then used to identify similarities between the query image (Q) and the target images (T) in the database, formulated as follows;

$$S(Q,T) = \frac{\sum_{k=0}^{n-1} \min\left(H_k^Q, H_k^T\right)}{\sum_{k=0}^{n-1} H_k^T} \tag{4}$$

where H_k^Q and H_k^T are the histogram of the query image and the target image, respectively, and n is the number of bins for each histogram.

4 PRACTICAL APPLICATION

4.1 Datasets

While most image retrieval research has focused on general image databases such as the Corel collections or MPEG-7 datasets, for this study personal photograph collections were used to enable important clues pertaining to geo-coded image content to be utilized. The image database consisted of 1 750 images belonging to 10 classes that have been rescaled to 640×480 JPEG format before performing feature extraction. In this study, the classes were segmented to generate the ground truth for evaluation, and used only to calculate the effectiveness of the new approach. In the experiment, retrieved images were considered to be relevant if they belonged to the same class as the query image.

Nikon D2X/H products support recording the latitude, longitude and altitude of pictures taken when the product receives GPS data from valid sources in the NMEA-0183 protocol. In order to generate the geo-coded image collection, a Nikon D200 connected to a GPS receiver with a MC-35 adapter cable was used as the camera module. A GX-325 based on the SiRF start III SP chipset manufactured by SiRF Corporation linked via RS-232C port was used as the GPS module. The system stored the set of geo-location coordinates and their place names based on GPS image file directories defined by the EXIF specification [19].

Because GPS requires a line-of-sight connections with the satellites, the signal can be lost inside buildings or in heavily built-up areas. While it is possible to integrate the cell ID from mobile phone or advanced indoor GPS technology, this issue was not addressed in this study. Instead, consecutive photos (i.e., p_m) with no location information were assumed to belong to the same GPS track.

$$(p_l, p_n \in C_i \wedge (time(p_l) < time(p_m) < time(p_n))) \Rightarrow p_m \in C_i$$

4.2 Experimental Results

The most common evaluation measures used in information retrieval (IR) are precision and recall, usually presented as a precision-recall curve [20]. Precision denotes the fraction of all possible relevant images retrieved and recall indicates the fraction of the images retrieved that are actually relevant to the query, calculated using the following equations

$$\begin{aligned}\text{Precision} &= \frac{\text{the number of relevant images retrieved}}{\text{the number of relevant images in collection}} = \frac{a}{a+b}\\ \text{Recall} &= \frac{\text{the number of relevant images retrieved}}{\text{the number of images retrieved}} = \frac{a}{a+c}\end{aligned} \tag{5}$$

where a is the number of relevant images retrieved, b is the number of relevant images that were not retrieved, and c is the number of irrelevant images retrieved.

Because precision and recall are not always the most appropriate measures for evaluating IR, the precision and recall scores are often combined into a single measure of performance, known as the *F-score* [21]. Higher values of F-score are obtained when both precision and recall are higher. The formula for F-score is

$$Fscore = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{6}$$

The following experimental approach was adopted to evaluate the search results and quantify any improvement in the retrieval performance due to the integration of geo-coded content analysis, compared to that of a search using content analysis alone. Leave-one-out cross validation (LOO-CV) performance was applied to obtain more reliable estimates compared to other experiments where the results are based on a small number of queries, for example MPEG-7 [17]. Thus, each image in the database was selected in turn as the query image, and queried against the remaining images.

The results of a retrieval using the flat layer of spatial-temporal index are given in Figure 4. Figure 4 a) shows the measurement using $t = 0$ (described in Equation (1)) corresponding to the spatial filtered set prior to ranking retrieval, while Figure 4 b) displays the results for $t = 1$ to evaluate the temporal filtering process. As the graphs illustrate, in both tests the approaches using the new spatial-temporal index significantly outperformed location-only and time-based retrievals. Looking at the effect of differences in the removal parameters for distance and time interval, distance from the given location had more impact than capture time for retrieval performance, probably due to the fact that the images were captured in bursts many days apart, which is typical of recreational photographers. As a time series, most of the personal photos were thus taken within a specific time range. The results of the proposed G-CH and G-EHD within 5 km and 10 km of the query image shared the same value for retrieval performance, probably because most of the images in the same location cluster were captured relatively close to each other in this dataset.

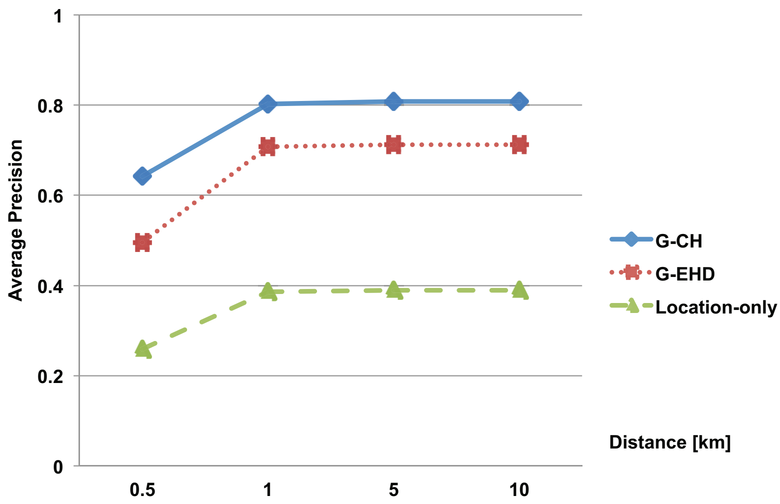
Figure 5 shows the results for the comparison of retrieval effectiveness over all the query types. The parameter values for G-CH and G-EHD were 1 km (ε) and 1 week (μ). The values shown were computed in terms of precision and recall after the top 100 images had been retrieved, denoted as P(100) and R(100), respectively. The combined approaches on both the flat and hierarchical layers had significantly better F-scores compared to the system utilizing only content-based ranking retrieval (CH and EHD). Comparing CH with G-CH, CH included a higher proposion of irrelevant images during the search, indicated by its low-precision and high-recall. Based on the average from all queries for F-score at G-CH and G-EHD, 80 % and 71 % of all relevant images in the database were retrieved, whereas CH and EHD retrieved only 53 % and 47 % of the relevant images in the image collection. The results for this dataset also confirm that the retrieval performances using the hierarchical layer, which select photographs that are in the same level of hierarchy (in this case with the district as the 4th level), are as effective as those filtering based on distance from the query image. These results revealed that HG-CH and HG-EHD both exhibited a slight improvement in retrieval effectiveness.

Figure 6 shows the top 10 ranked results for each retrieval method, using a location-based filtering parameter of 1 km. It is interesting to note that the proposed methods both retrieved fully relevant images, several inappropriate images were returned by the location-only method (ranked at 2, 3 and 8). This was because although the images were taken at the same place, the camera was pointing in a different direction and/or had a different zoom setting and was thus focused on a different image.

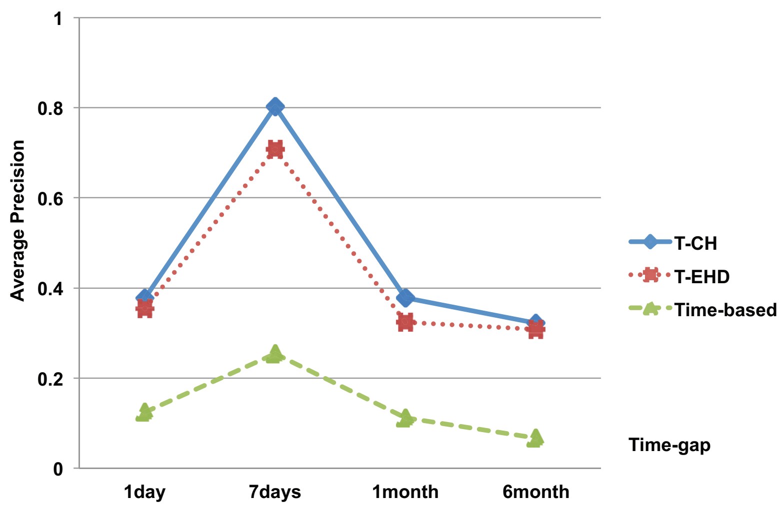
Table 1 shows the computational characteristics of each method. The extraction time for an image and the retrieval time for relevant images over the entire database (1 750 images) were computed using an Intel Core 2.66 GHz machine with 2 GB RAM. Even through the proposed methods (G-CH, G-EHD, HG-CH and HG-EHD) required little more computing time and storage in comparison to other methods (CH and EHD), they were noticeably more accurate when applied to an image search within a reasonable time and system resource allocation.

5 CONCLUSIONS

This paper introduced a new method that creates an index for photographic image retrieval using geo-coded information, specifically the GPS-derived position and the date/time at which the image was captured. The new approach utilizes two-layer indexes containing spatial and temporal information that are generated automatically for each image. An experimental evaluation showed that the proposed method significantly improved image retrieval performance compared to existing search algo-



a)



b)

Fig. 4. Comparison of retrieval effectiveness using average precision over all queries. a) Average precision for location filter (ε). The proposed G-CH and G-EHD indicate the addition of location-based filtering prior to ranking retrieval for CH and EHD, respectively. b) Average precision for time filter (μ). T-CH and T-EHD denote the addition of time-based filtering prior to CH and EHD, respectively.

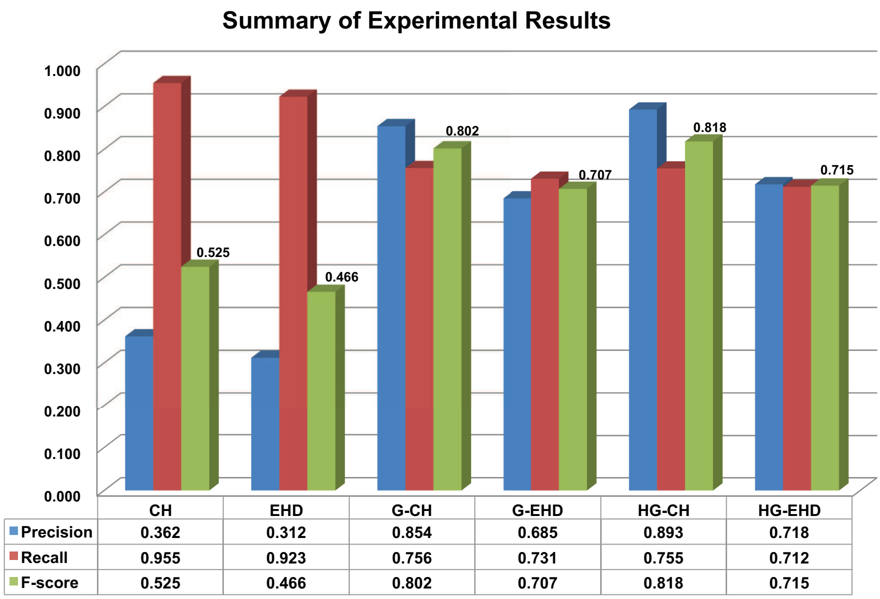


Fig. 5. Comparison of retrieval effectiveness using F-score over all queries. HG-CH and HG-EHD denote prior selection based on the hierarchical layer, namely CH and EHD, respectively.

Method	*Feature Extraction Time* [sec/image]	*Retrieval Time* [sec/image]	*Length for Storing Feature* [byte/image]	F-score [%]
CH	0.373	0.047	128	52.5
EHD	0.519	0.028	80	46.6
G-CH	0.402	0.082	140	80.2
G-EHD	0.572	0.046	92	70.7
HG-CH	0.464	0.321	208	81.8
HG-EHD	0.687	0.293	160	71.5

Table 1. Summary of computational characteristics of the methods

rithms. Based on these findings, applying combination of context and content-based features to image search functions offers a valuable new way to deal with an increasingly important issue.

The key contribution of this paper lies in its combination of geo-location-based and content-based visual features to improve the performance of retrieval methods incorporating automated indexing for large collections of photographs. Ubiquitous computing environments provide an new and exciting avenue for information retrieval, but one of the challenges currently limiting many applications is how to best

Fig. 6. Top 10 ranking lists for each retrieval method. The query image is at the top-left.

provide relevant information to users in real time through location-aware services. The ability to identify relevant images using a combination of geo-information and visual features may provide a basis for more general methods of retrieval.

In future research, we plan to test the performance of the system proposed here for larger scale databases and then go on to extend it to incorporate other metadata such as temperature or weather conditions. This would allow users to search for photographs associated with specific atmospheric conditions such as "sunrise/sunset" or "rainy/sunny". In addition, we expect to apply this new approach to other types of images such as graphic images using the recording instrument's IP address rather than geographic coordinates.

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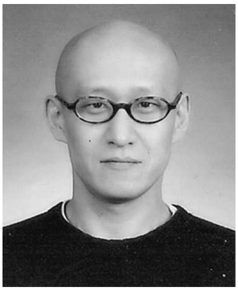

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