iPixel: A visual content-based and semantic search engine for retrieving digitized mammograms by using collective intelligence

Giner Alor-Hernández¹, Yuliana Pérez-Gallardo¹, Rubén Posada-Gómez¹, Guillermo Cortes-Robles¹, Alejandro Rodríguez-González² & Alberto A. Aguilar-Laserre¹

¹Division of Research and Postgraduate Studies, Instituto Tecnológico de Orizaba, Orizaba, Mexico and ²Computer Science Department, Universidad Carlos III de Madrid, Madrid, Spain

Abstract
Nowadays, traditional search engines such as Google, Yahoo and Bing facilitate the retrieval of information in the format of images, but the results are not always useful for the users. This is mainly due to two problems: (1) the semantic keywords are not always useful for the users. This is mainly due to two problems: (1) the semantic keywords are not taken into consideration and (2) it is not always possible to establish a query using the image features. This issue has been covered in different domains in order to develop content-based image retrieval (CBIR) systems. The expert community has focussed their attention on the healthcare domain, where a lot of visual information for medical analysis is available. This paper provides a solution called iPixel Visual Search Engine, which involves semantics and content issues in order to search for digitized mammograms. iPixel offers the possibility of retrieving mammogram features using collective intelligence and implementing a CBIR algorithm. Our proposal compares not only features with similar semantic meaning, but also visual features. In this sense, the comparisons are made in different ways: by the number of regions per image, by maximum and minimum size of regions per image and by average intensity level of each region. iPixel Visual Search Engine supports the medical community in differential diagnoses related to the diseases of the breast. The iPixel Visual Search Engine has been validated by experts in the healthcare domain, such as radiologists, in addition to experts in digital image analysis.

Keywords: CBIR, collective intelligence, iPixel, mammograms

1. Introduction
Information retrieval of image collections on the Internet is not a new topic. Different approaches have been proposed in order to improve the information retrieval performance, including text-based methods, such as AltaVista, and link-based methods, such as Google’s PageRank [1]. However, the development of content-based image retrieval (CBIR) systems has been less studied. Nowadays, large collections of images are available to Internet users, and traditional search engines such as Google, Yahoo and Bing have facilitated the information retrieval of images, but the results are not useful for all users.

Correspondence: Giner Alor-Hernández, Division of Research and Postgraduate Studies, Instituto Tecnológico de Orizaba, Av. Oriente 9, No. 852, Col. Emiliano Zapata C.P. 94320, Orizaba, Mexico. Tel: +272 7257056. Fax: +272 7257056. E-mail: galor@itorizaba.edu.mx

Informatics for Health and Social Care, September 2012; 37(3): 159–176
Copyright © Informa UK Ltd
ISSN 1753-8157 print/ISSN 1753-8165 online
DOI: 10.3109/17538157.2012.654840
This is due to two main problems: (1) semantic keywords are not taken into consideration: when a user provides an ambiguous keyword to this search engine, the response is formed by all its different and possible meanings, while the user is probably interested in only one of them. This ambiguity is generated by polysemy and synonymy and (2) it is not possible to define a query concerning the image content because people tend to describe images based on objects that are shown in them, and this type of description produces results of correspondence between human perception and image content. This issue has been covered in different domains and has led to the development of CBIR systems. Examples of these domains are customer relationship mangement (CRM) and e-commerce where it improves the customer experience by allowing the customer to search for products in a more interactive way. For instance, Google Goggles recognizes the object that has been captured using a camera phone and returns products with similar images and relevant information about the object. Recently, the expert community has focussed their attention on the healthcare sector, where there a lot of visual information, such as X-rays, mammograms, MRI’s, CT scans and others are available for medical analysis. Image production grows at a faster rate than the methods used to manage and process said information, provoking a new challenge to improve representation, storage and information retrieval. Nowadays, collective intelligence (CI) is an active field of research based on the principle that each person knows about something, and therefore nobody has absolute knowledge. For this reason, the incorporation and participation of the knowledge of every stakeholder are essential in order to capitalize on the CI dimension. The CI definition used in this work was coined by the Massachusetts Institute of Technology Center for CI:

Groups of individuals doing things collectively that seem intelligent [2].

For a better explanation of the definition of CI, we can analyze both of the terms:

Collective: It is anything where multiple and interactive entities are involved.

Intelligence: Psychologists say intelligence is a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience.

Therefore, CI is the capacity of human collectives to engage in intellectual cooperation in order to create, innovate and invent [3]. This can be applied in a variety of different contexts such Web 2.0 or social computing where users are invited to interact and participate in designing and creating the information that they use. This paper presents an innovative solution to problems of semantics and content for undertaking digitized mammograms searches using CI and implementing a CBIR algorithm. CBIR is a very dynamic field of research which is continually expanding. CBIR is a technique used to retrieve images based on their visual properties. The goal is to find, in an efficient way, images in a database that are similar to a target image. Unlike the typical queries in databases, a criterion of similarity is used which does not necessarily provide an exact match [4]. The different key paradigms of CBIR are described as following:

Query by visual example (QBVE) is the traditional type of query used in CBIR. Its starting point is a visual example provided by the user: a set of images with a strict visual matching of the image query retrieved. Concordance analysis is carried out by reviewing the similarity of the features extracted from a visual example versus features previously obtained from the images that are either within the database or a repository. These features range from color histograms, level intensity, texture or other aspects, which were obtained using the old systems of retrieval. Now, the most sophisticated representations of those features are used in modern systems for optimal image retrieval [5]. The main disadvantage of this approach is the existence of many queries in which the visual similarity does
not correlate strongly with human similarity judgments. This leads to semantic differences between users and machines. This mismatch between judgments of similarity makes user interaction with any QBVE system a frustrating one. Most people are not able to justify the results returned despite the obvious similarities of visual stimuli. This is a worrying scenario for the recovery of low-level images.

Semantic retrieval (SR). For this approach, the image content is queried through the provision of a keyword by the user. It seeks to recover images that contain a semantic concept associated with the keyword; this builds a higher-level abstraction than natural language queries. The disadvantages of SR include: (1) the tag associated with the image does not truly represent the property of the referenced image; (2) it is not known which regions of the image are associated with each tag; (3) problem of lexical ambiguity, due to the fact that multiple meanings are associated with the same word; (4) multiple semantic interpretations for an image and (5) vocabulary limited by size. A tag has a limited assigned size and it is not able to withstand any concepts out with its range. Despite its many disadvantages, SR is useful in creating high-level abstractions that handle the semantic problem of the QBVE approach well. In order to overcome the disadvantages of this approach, query by semantic example (QBSE) was incorporated and is described below.

QBSE combines the best of both QBVE and SR. A QBSE system works on a semantic level. Images are tagged using a lexicon of visual concepts, just like SR. Then each image is mapped via a weights vector of all the semantic concepts using a semantic tagging system. The concepts are elements of a previously defined lexicon. Retrieval is based on the query-by-example paradigm: the user provides a query image, and then the weights vector matches the vectors in the database using a suitable similarity function [6]. This approach is the most widely used and robust; for this reason, this technique was selected for our proposal.

Our proposal allows users to be responsible for managing the existing information, so the user community obtains a useful means of creating and sharing knowledge. As a case study, we have reported on the retrieval of medical images (digitized mammograms) to eliminate problems concerning semantic content. Our Web-based application was developed using friendly interfaces, where medical specialists can easily identify mammograms with similar semantic and physical features.

2. State of the art

The CI approach facilitates the creation of collaborative knowledge by encouraging members to share opinions and arguments concerning the issues within the collective improvement mechanism. CI covers different fields, one of them being education. DDtrac [7] is a special education CI application that uses student-specific data to support decision-making, collaboration and an improved understanding of the unique education needs of individual students. This application provides the special education team with the opportunity to harness the knowledge of these students in order to identify patterns of behavior and best practices for both individual students as well as groups of students with similar disabilities. Verayuth et al. [8] present another example of CI application: Knowledge Unifying Initiator for Herbal Information (KUIHerb) is a platform which aims to build a Web community for the collection of intercultural herbal knowledge using the concept of a CI. The herb identification, herbal vocabulary and medicinal usages can be collected from this system. They use three strategies: providing a set of technical terms in Thai that can be added into the dictionary, which use Thai word segmentation in order to improve the indexing process; a set of synonyms of these technical terms in both Thai and English is created in order to help users form keywords from the same term; and a set of keywords from herbal usages that can be combined with the name keyword.
In the last few years, researchers have focussed their efforts on proposing effective methods to obtain information and retrieve images from the Web. IntelliSearch [9] is an automated system for retrieving text and images from the Internet. It supports the retrieval of Web pages and images and can be searched using semantic similarity in order to find information relating to the needs of the users. It uses text-based methods such as vector space model and semantic similarity retrieval mode, which are far more effective than link-based analysis methods. IntelliSearch is currently being expanded to support queries through content-based images. Channin et al. [10] present the annotation and image markup (AIM) project. This project focusses on developing a mechanism for modeling, capturing and serializing image annotation and markup data that can be adopted as a standard by the medical imaging community. The AIM project produces both human and machine-readable artifacts, unlike DICOM [11] which offers little about the content or meaning of the pixel data. The AIM project provides developers with a toolkit that enables them to adopt AIM in their applications. AIM provides a foundation for standardized image annotation practice in the clinical, research and translation communities. Bindelli et al. [12] present TagOnto, a folksonomy aggregator, which combines the collaborative nature of Web 2.0 with the semantic features provided by ontologies in order to improve the user experience when searching and browsing the Internet. The goal of the TagOnto system is to function as the bridge between mapping tags, which is a social activity, and more structured domain ontologies, thus providing assistive, navigational features typical of the semantic Web. The TagOnto components are a multi-folksonomy, tag-based search engine and an ontology-based query refinement facility which exploits domain ontology to filter results and to focus users’ attention. Anagnostopoulos et al. [13] propose an AJAX-based image meta-search engine for providing more precise search results for queries that concern images with human appearance. It uses some fuzzy logic rules to identify possible human presence and an artificial neural network for face detection, in order to achieve more specific results. In each search, the user can store their preferences. This proposal has limitations in terms of image type, size and illumination conditions. This system is performed locally on the client-side. Baeza-Yates et al. [14] present a set of tools for: efficient Web-crawling, content-based image analysis (low-level features such as color, shape and texture), skin segmentation, face detection and Web pages clustering using text information on specific Web collections. This application is not yet complete. Liu et al. [15] present a new method to increase user experience during image searches, browsing and navigation on mobile devices. This is possible by clustering result images based on visual and semantic meaning. User can see the overview of the search results with only a few clicks so as to speed up the navigation process. For images, an optimal layout algorithm is used: the summary of each cluster is presented on a small screen with maximum scaling ratio and the information remaining is shown to users on a limited screen. Batko et al. [16] developed an experimental similarity search system based on a test collection of more than 50 million images. They focussed on two strictly related challenges of image scalability: (1) to obtain a collection of images with the corresponding descriptive features and (2) to develop indexing and search mechanisms capable of scaling to the target size. The images were taken from the Flickr photo-sharing system and GRID technology (a dynamic environment that allows to transparently run a given application on a large set of machines) for extracting five descriptive features for each image that was used. They have also proved a distributed content-based retrieval system that offers a search for visually similar images which provides a response in usually less than 1 s. In addition, they have also created a Web interface that allows regular users to interact with the system and search for similar images. Liu et al. [17] provide a survey of the technical achievements within the research area of
content-based tag processing for social images. They cover the research aspects on tag ranking, tag refinement and tag-to-region assignment. They present a brief suggestion for future promising directions, like cross-modality content analysis, visual understanding using tag cues, efficient manual tagging system design and scalable automatic tagging. Sasso et al. [18] developed a visual query-by-example image database for storing and retrieving chest CT images by means of a visual browser image management environment (IME). This system is a tool for clinical practice which facilitates searches for different radiological tasks. The visual browser IME included four fundamental features (segmentation, indexing, quick load and recall and a user-friendly interface); currently, this system is under evaluation as an experimental application. Depeursinge et al. [19] describe an overview of requirements for building an image-based diagnostic aid with secondary data integration. They use clinical parameters and high-resolution computed tomography (HRCT) images for diagnosing interstitial lung diseases. The system analyzes visual features for classification of lung tissue patterns. The group also built a multimedia database which provides validity in terms of training and the diagnostic aid system.

These initiatives suffer from several drawbacks, such as: (a) they require prior knowledge on how to behave under each situation; (b) there is a lack of usage for advanced capabilities of rich Internet application technologies and (c) there is a lack of standardization in terms of the terminology used.

These deficiencies can be improved by: (a) using IC to retrieve community knowledge, in this way ensuring that the knowledge database increases quickly; (b) creating friendly and easy-to-use application interfaces which are necessary in order to improve the user experience (RIA applications have these feature) and (c) using standard context dependent semantic classification for the terminology. This approach offers several benefits to the medical community where the use of CI in combination with CBIR algorithms can be employed as a strategy to capitalize on available knowledge and to support differential diagnostics related to the breast.

3. **iPixel – a visual search engine: architecture and functionality**

The **iPixel Visual Search Engine** is an innovative solution to recover digital mammograms based on semantic and visual content. The **iPixel Visual Search Engine** supports the medical community in differential diagnoses related to the breast. **iPixel** is available at http://innovasolver.com:8080/ipixel. In the following section, we present the **iPixel** architecture explaining the **iPixel**’s functionality.

3.1. **Application architecture**

The **iPixel Visual Search Engine** is a Web 2.0 application with a layered design that allows scalability and easy maintenance as its tasks and responsibilities are distributed. In Figure 1 the **iPixel** application architecture is shown, highlighting the different interrelated components needed to carry out the three main workflows of the application: (1) loading image, (2) collective tagging and (3) CBIR. The components are distributed among the different layers to improve the overall performance of the application. The **iPixel**’s workflows are described in the following subsections.

3.1.1. **Upload image workflow**

This workflow manages the set of images. It is composed of image analysis and image controller modules. **iPixel** is used for the recovery of content-based digital mammograms. **iPixel** supports image cytometry standard (ICS) images. The ICS format file can store:
Multidimensional and multichannel data.
Images in 8, 16 or 32 bit integer, 32 or 64 bit floating point and floating point complex data.
All microscopic parameters directly relevant to the image formation.
Free-form comments.

The ICS format uses two kinds of files: (1) a text file with .ics extension that has the header and (2) another file with .ids extension that is much larger and which contains the real image data. The images files have size ranges from $3,724 \times 6,188$ to $2,044 \times 5,894$ pixels, and file sizes of 23-44 MB. ICS format files are analyzed in their original format to ensure quality. If the files are reduced in size, quality would be also degraded. The digitized mammograms used by iPixel were obtained from The mini-Mammographic Image Analysis Society (MIAS) database of mammograms [20].

This workflow starts when the user loads an image with an ICS format file to the application server through an FTP service due to the image size, where it is then directed to the image analysis module. The image analysis module opens the ICS file to retrieve the image features, shows them to the user and finally stores them in a database.

3.1.1.1. Getting visual features. After opening the image, it is necessary to obtain the visual features through different image-processing operations, such as image binarization, the application of filters and low-level analysis to detect regions of interest. In order to carry out these operations, ImageJ library was used in order to manipulate the ICS format files. ImageJ is a Java-based library for image processing. ImageJ was developed by Wayne Rasband at the National Institute of Health in the USA (NIH) [21,22]. The operations for retrieving visual features are described below.
Image binarization and segmentation: Image binarization is also known as the threshold method [22]. This method has the goal of separating the objects of interest from the remainder of the image, as shown in Figure 2. The image binarization process is achieved by assigning each image pixel to one of the two groups (0 or 1); in this way the gray level of each pixel is compared with the threshold value. If this gray level is less than the threshold value, this pixel belongs to group 0; if not, it belongs to group 1. There are different methods to image binarization, the most common being the Otsu method. This method calculates the threshold value so that the dispersion within each segment is as small as possible, but, at the same time, ensures that the dispersion is as high as possible between different segments [21]. A novelty in iPixel is the use of a staggered binarization technique that leaves the expert to decide what threshold level is the most adequate for a particular image. This is important for medical experts as the mean mammographic gray levels depend on acquisition conditions, so a semi-automatic binarization method leaves the expert to decide the most adequate threshold for each acquisition. iPixel scans the image three times with different threshold values (70, 100 and 140). This is due to the difference in the average intensity levels of our images. These values were selected through heuristics with 100 tests on a random image and were backed up by the expert. The results obtained proved to be adequate values to ensure high proficiency technique.

Applying filters: The filters have the goal of eliminating those image elements that may affect the process of identifying regions of interest, for example, the limit of acquisition window surrounding the area of interest. In iPixel, it is necessary to apply the following three procedures:

- Windowing: which entails adjusting the image’s working area to the real area of interest which is generally a smaller area that contains the tissues to be analyzed. In order to achieve this, the expert can select the area to be labeled.
- Erosion filter: this thins the edges of an image. In this case, the smaller regions of the image, that could be caused by noise during the acquisition system, are removed, leaving the dark regions highlighted.
- Dilation filter: which expands the edges of the image. In general, it is complementary to the erosion filter, highlighting the white regions of the image.

A low-level analysis to detect regions of interest: The next step is detecting regions of interest on an image by using a marking algorithm. There are different methods for searching binary regions, such as region marking through flood filling (a region is filled in all

![Figure 2. Image binarization.](image-url)
directions starting from a single point, or ‘seed’, within the region) or region sequential marking [22]. In iPixel, a variant of the latter is used. The algorithm takes a binarized image and evaluates it pixel-by-pixel from left to right and from top to bottom. This algorithm takes a decision regarding each pixel and assigns a value depending on the values of the neighboring pixels, as shown in Figure 3, where CP is current pixel, TP is the top pixel and LP is the left pixel. At the end of the algorithm, the number of different values assigned equals the number of regions of the image.

In Figure 4, the conditions for the marking algorithm are shown:

- If CP is a background pixel (value 0), nothing is done.
- If CP belongs to an object (value 1), it makes a decision based on the TP and LP values, as follows:
  - Seeding a new value. When TP and LP are image background, a new value is seeded, i.e. a new object is found, the marking counter values are incremented by 1 and it is assigned to CP.
  - Lateral propagation of color. When TP is image background and LP is object, the LP value is spread to the current pixel.
  - Vertical propagation of color. When LP is image background and TP is object, the TP value is spread to the current pixel.
  - Crossing regions. When the TP and LP are both objects, their values are checked. If they are equal, one of them is spread, but if they are different, the regions are united and the lower value dominates. The lower value is set to the current pixel.

Once all of the regions have been identified, all of those with an area of less than 400 pixels are discarded. Finally, the image and the features suggested are sent to the tagging module, which shows the suggestions to user for the collective tagging process.

3.1.2. Collective tagging workflow

The purpose of this workflow is to build a collective tagging system where users choose tags with semantic meaning to describe the image content. The classification created is a taxonomy. This workflow starts in the module called client-side feedback. This module is used for adding or changing tags with semantic meaning to the images in order to describe their content. In this context, the image features are the tags associated with it. CI is used on the collective tagging system to increase the user community knowledge, due to the fact that every user contributes his/her own knowledge to the collectivity for the benefit of all. We have proposed a classification scheme for tagging as shown in Figure 5. This classification is based on Breast Imaging Reporting and Data System (BIRADS). The BIRADS provides a standardized classification for mammographic studies. The BIRADS classifications are divided into an incomplete assessment (category 0) and completed assessments (categories 1, 2, 3, 4, 5, 6) [23], where:

![Figure 3. Neighboring pixels.](image)
BIRADS 0: Describes an incomplete assessment.
BIRADS 1: Describes a negative assessment.
BIRADS 2: Describes a benign finding.
BIRADS 3: Describes a probable benign finding.
BIRADS 4: Describes a suspicious abnormality.
BIRADS 5: Describes a highly suspicious malignancy; appropriate action should be taken.
BIRADS 6: Describes a known biopsy-proven malignancy; treatment pending.
Once the appropriate BIRADS has been detected, it is necessary to classify it within the following categories:

- skin,
- vascular,
- suture,
- thickness,
- shape of stick,
- round,
- spherical,
- branched,
- amorphous,
- border.

And finally, the classification by distribution within the following types:

- grouped,
- segments,
- regional,
- disseminated diffuse,
- multiple groups,
- linear.

*iPixel* proposes this classification scheme for tagging mammograms due to the BIRADS method, which enables the suitable classification of breast injuries, develops a radiological protocol for greater certainty in mammogram diagnostics and also allows terminology standardization [24,25].

### 3.1.3. Recovery of images based on content workflow

The goal of this workflow is to retrieve a set of content-based images. In this workflow, the semantic content and visual content search modules are located, the functionality of which is described below.

#### 3.1.3.1. Semantic content search

This workflow starts when the user requests a semantic content-based search and they establish a keyword which is sent to the semantic feature analysis module where it is redirected to two modules: (1) the semantic analysis module and (2) the search for images with similar semantic features module. CI with a recommendation mechanism is used in the semantic analysis module, where each search is weighed up and, through a tag cloud, the most searched for context is
suggested. Based on this suggestion, the user can define the semantic meaning of their searches. In the SSFIS module, the images in the database, which are associated with a similar tag to the criteria defined by the user, are searched for.

3.1.3.2. Visual content search. The iPixel Visual Search Engine also allows three kinds of visual content-based searches: (1) searching by number of regions per image; (2) searching by maximum and minimum size of regions per image and (3) searching by average intensity level of each region. The comparisons are carried out by measuring the Euclidean distance between the selected image and each image stored in the database. Euclidean distance was selected due to its simplicity to calculate the distance between two points from a multidimensional point of view. Furthermore, it determines how similar two items are in percentage terms. iPixel only shows the results that have a percentage of similarity higher than 80%. This similarity level was defined by consensus with the expert panel.

4. Case study: a content-based search for retrieving a digitalized mammogram

The iPixel Visual Search Engine is used for resolving issues in the retrieval of digital mammograms based on semantic and visual content by using CI mechanisms. iPixel supports the medical community in differential diagnoses relating to diseases of the breast. The iPixel Visual Search Engine is validated not only by experts in the field of medicine (i.e. radiologists), but also by experts in digital image analysis. To explain the operation of iPixel Visual Search Engine, the following case study for a content-based search for retrieving a digitized mammogram is presented.

Let us suppose that a user has a digitized mammogram, as shown in Figure 6, which shows calcinosis, but they also want:

(a) To validate the diagnosis.
(b) To see all the mammograms with a similar semantic meaning; in this case they are looking for regional distribution.

For point \(a\): in a normal case, the user searches for patient records diagnosed in the same way and compares their mammograms. This action has some disadvantages: (a) the records are not available; (b) they do not present similar calcification and (c) the time

![Figure 6. Original digitized mammogram.](image)
required to search is too long. We propose using *iPixel Visual Search Engine* as an alternative solution to this problem.

By using *iPixel*, the user uploads the ICS format file to the application server by using an FTP service. In *iPixel*, the user clicks on the *Load Image* button where the application displays a list of all ICS files that are in the FTP directory as shown in Figure 7. Next, the user selects a file to check and, with this selection, *iPixel* makes a suggestion about the image sectors that have any calcinosis and/or tumors, as shown in Figure 8. These sectors are called regions of interest.

![List of files on the *iPixel*’s FTP directory.](image1)

![Regions of interest.](image2)
In this interface, the user can add, delete or modify regions of interest as they see fit, according to their own experience. The user can also add tags that describe the selected feature as shown in Figure 9.

When the image and its regions of interest are stored, iPixel compares them with other regions. The user has two options to compare the original region with image regions stored in the database: (1) searching by similar size and (2) searching by similar average intensity as shown in Figure 10a and b, respectively.

For point b, in a normal case, the user searches for patient records diagnosing regional calcinosis and they compare their mammograms. There are some disadvantages: (1) the records are not always available and (2) the time required to search is too long or the diagnosis could be wrong. An alternative solution to this problem is the use of iPixel Visual Search Engine for retrieving images with similar semantic and visual meaning. First, the user should type the word ‘regional’ in iPixel and then they should click on the search button. iPixel will show all the images that have a region tagged with the same word, as shown in Figure 11.

iPixel considers all the user searches, i.e. for each search, iPixel increases the weight of each item or searched word. With the values obtained, iPixel suggests the most searched words by a tag cloud. This tag cloud helps the user to define the semantic meaning of their search. iPixel shows the user the search results and provides an images preview, as shown in Figure 12. Furthermore, iPixel presents three types of search options: (1) by image numbers of regions; (2) by maximum and minimum size of image regions and (3) a view of the tagged regions.

The results of these three types of searches are displayed on the interface, as shown in Figure 13. While the view of the regions tagged is shown in Figure 14, it is noteworthy that in the tagging view, the user can add, edit and delete image regions as the user sees fit.

This case study shows the usefulness of the iPixel Visual Search Engine application as an alternative to search for content-based medical images where CI is used within a Web 2.0 application. iPixel is useful for users who want to retrieve images with a similar visual and semantic meaning, by using the knowledge and experience of other users.
It is important to stress that the user community, which uses the iPixel application, has a responsibility to truthfully select and tag images, as indicated by the CI philosophy: the member community’s inputs refine the product obtained from the collective contribution.

5. Evaluation

A benchmarking process was undertaken in order to measure the iPixel Visual Search Engine’s performance. This test was made to recover images within iPixel Visual Search Engine, where different iPixel searches were analyzed: (1) by number of regions per image and by maximum and minimum size of regions per image; (2) by average intensity level of each region and (3) correct tagging.
1. Searching by number of regions per image and by maximum and minimum size of regions per image: The error ratio for these searches was zero due to the fact that the values for calculating the Euclidian distance of each image, like the number of regions and the maximum and minimum size of regions, are stored in the database, which offers precise results.

Figure 12. Image preview.

Figure 13. Searching by minimum size of image regions.
2. **Searching by average intensity of each region level**: In this test, the search’s accuracy was analyzed. As the nature of this search is the average level of intensity by region, there is a certain degree of error. For instance, if we have a region, as shown in Figure 15a, which has an average intensity of 50, it tends to be gray. If *iPixel* compares this region with another region whose average intensity level is also 50, but which has a different distribution of intensity levels, such as shown in Figure 15b, *iPixel* takes the two regions with a similarity percentage of 100%. The search algorithm was implemented in a representative set of images. The results presented an error rate of 8% according to the expected results.

3. **Correctness in tagging system**: There is a possibility that some users incorrectly tag a region within an image. Fortunately, *iPixel* uses CI, which helps to correct these errors.
errors by using feedback from other users, i.e. the more the users contributing to the tagging system, the more accurate our application.

6. Future directions

In terms of future work, we are implementing a reputation system for users who participate in the tagging of images. With this it is possible to know how reliable are their opinions when tagging images, which in turn leads to the development of a module in which users are registered. This reputation should stem from ratings in different surveys undertaken by other users who perform searches and express their opinions about the certainty of these tags. We also suggest an ontology implementation for storing relationships among images and concepts tagged, thereby iPixel could make some kind of inference about the information stored.

7. Conclusions

Due to the large collections of images available to Internet users, there is a need to obtain information about them by using CBIR techniques. This need arises also in the medical field where there is a lot of visual information such as X-rays, mammograms, MRI’s, CT scans and others, which are available for medical analysis. The iPixel Visual Search Engine is an innovative retrieval solution for digital mammograms based on semantic and visual content by using CI and implementing a CBIR algorithm. Furthermore, iPixel allows users to be responsible for managing the existing information, so the user community obtains a useful means of creating and sharing knowledge. Our Web-based application was developed using friendly interfaces, where medical specialists can easily identify mammogram features with similar semantic and physical features. iPixel offers several benefits to the medical community where the use of CI can be employed as a strategy to capitalize knowledge and to support differential diagnostics.

Acknowledgements

The authors give special thanks to The mini-MIAS database of mammograms (http://peipa.essex.ac.uk/info/mias.html) for providing all digitized mammograms used by iPixel. iPixel follows the licence agreement established by the MIAS on the use of the mammograms database for research purposes.

Declaration of Interest: The authors report no conflicts of interest.

This work was supported by the General Council of Superior Technological Education of Mexico (DGEST). Additionally, this work was sponsored by the National Council of Science and Technology (CONACYT) and the Public Education Secretary (SEP) through PROMEP (Teacher Improvement Program or Programa de Mejoramiento del Profesorado, in Spanish).

References


© Informa UK Ltd


21 Ferreira T, Rasban W. The ImageJ user guide. Montreal, Canada: Centre for Research in Neuroscience, McGill University; 2011.


