International Journal of Emerging Technology in Computer Science & Electronics (IJETCSE)
ISSN: 0976-1353 Volume 11 Issue 5 –NOVEMBER 2014.

A NOVEL APPROACH ON IMAGE RETRIEVAL WITH LBP OPERATOR

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Abstract— Images are being used since many years in all spheres including Forces, Treatment of injuries and diseases etc. But in the past few years, number of images has increased in huge amount due to the growth of web database. So, in vast and varied collection, users of different domains face a problem of retrieving images relevant to the user query. The LBP operator is defined as a grayscale invariant texture measure, derived from a general definition of texture in a local neighborhood. Through its extensions, the LBP operator has been made into a really powerful measure of image texture, showing excellent results in terms of accuracy and computational complexity in many empirical studies Due to its discriminative power and computational simplicity, the LBP texture operator has become a popular approach in various applications, including visual inspection, image retrieval, remote sensing, biomedical image analysis, motion analysis, environment modeling, and outdoor scene analysis. In this paper, we have examined the need for image data management, CBIR and image retrieving with LBP operator

Index Terms— Feature extraction, text and visual field, Local Binary Patterns, Image Retrieval, CBIR

I. INTRODUCTION

Image Retrieval is the science of locating images from a large database or image sequences that fulfill a specified image need. And the relationship between queries, images, meaning, and relevance is considered as a foundation for image retrieval system. With the passage of time many image retrieval systems have been developed. Text-based image retrieval and content-based image retrieval are the two techniques adopted for search and retrieval in an image database. Currently, most Web based images search engines rely purely on textual metadata. That produces a lot of garbage in the results because users usually enter that metadata manually which is inefficient, expensive and may not capture every keyword that describes the image. On the other hand, the Content Based Image Retrieval (CBIR) systems can filter images based on their visual contents such as colors, shapes, size or any other information that can be derived from the image itself which may provide better indexing and return more accurate results. This issue is the reason behind why the CBIR systems are not widely used for retrieving Web images. A lot of efforts have been made to bridge this gap by using different techniques called Multimedia In-formation Retrieval (MIR), TBIR (text-based image retrieval) systems can better capture the conceptual meaning of the question than CBIR. In Web medium, the

representation of images can be naturally split into two or more independent modalities such as visual features (color, shape, size) and textual feature Truly, we live in a multimodal world, and we as humans always take the benefit of each media for sensory interpretation to narrow the semantic gap problem and enhance the retrieval performance by fusing the two basic modalities of Web images, i.e. textual and visual features for retrieving. In digital images, the characteristics of a texture can be sensed via variations in the captured intensities or color. Although in general there is no information on the cause of the variations, differences in image pixels provide a practical means of analyzing the textural properties of objects. It is noted that "texture has been extremely refractory to precise definition". Later it simply: consider "a texture to be a stochastic, possibly periodic, two-dimensional image field. Texture analysis plays an important role in many image analysis applications. Even though color is an important cue in interpreting images, there are situations Where color measurements just are not enough — nor even applicable. In industrial visual inspection, texture information can be used in enhancing the accuracy of color measurements. In some applications, for example in the quality control of paper web, there is no color at all Texture measures can also cope better with varying illumination conditions, for instance in outdoor conditions. Therefore, they can be useful tools for high-level interpretation of natural scene image content. Texture methods can also be used in medical image analysis, biometric identification, remote sensing, content-based image retrieval, document analysis, environment modeling, texture synthesis and model-based image coding. In most applications, image analysis must be performed with as few computational resources as possible. Especially in visual inspection, the speed of feature extraction may play an enormous role. The size of the calculated descriptions must also be kept as small as possible to facilitate classification.

II. THE GROWTH OF DIGITAL IMAGING

The use of images in human communication is hardly new – our cave-dwelling ancestors painted pictures on the walls of their caves, and the use of maps and building plans to convey information almost certainly dates back to pre-Roman times. But the twentieth century has witnessed unparalleled growth in the number, availability and importance of images in all walks of life. Images now play a crucial role in fields as diverse as medicine, journalism, advertising, design, education and entertainment. Technology, in the form of inventions such as photography and television, has played a major role in facilitating the capture and communication of image data. But the real engine of the imaging revolution has been the computer, bringing with it a range of techniques for digital image capture, processing, storage and transmission which would surely have startled even pioneers like John Logie Baird. The involvement of computers in imaging can be dated back to 1965, with Ivan Sutherland's Sketchpad project, which demonstrated the feasibility of computerised creation, manipulation and storage of images, though the high cost of hardware limited their use until the mid-1980s. Once computerised imaging became affordable, it soon penetrated into areas traditionally depending heavily on images for communication, such as engineering, architecture and medicine. Photograph libraries, art galleries and museums, too, began to see the advantages of making their collections available in electronic form. The creation of the World-Wide Web in the early 1990s, enabling users to access data in a variety of media from anywhere on the planet, has provided a further massive stimulus to the exploitation of digital images. The number of images available on the Web was recently estimated to be between 10 and 30 million [Sclaroff et al, 1997] – a figure which some observers consider to be a significant underestimate.

III. THE NEED FOR IMAGE DATA MANAGEMENT

The process of digitisation does not in itself make image collections easier to manage. Some form of cataloguing and indexing is still necessary – the only difference being that much of the required information can now potentially be derived automatically from the images themselves.

The need for efficient storage and retrieval of images – recognized by managers of large image collections such as picture libraries and design archives for many years – was reinforced by a workshop sponsored by the USA's National Science Foundation in 1992 [Jain, 1993]. After examining the issues involved in managing visual information in some depth, the participants concluded that images were indeed likely to play an increasingly important role in electronically-mediated communication. However, significant research advances, involving collaboration between a number of disciplines, would be needed before image providers could take full advantage of the opportunities offered. They identified a number of critical areas where research was needed, including data representation, feature extractions and indexing, image query matching and user interfacing. One of the main problems they highlighted was the difficulty of locating a desired image in a large and varied collection. While it is perfectly feasible to identify a desired image from a small collection simply by browsing, more effective techniques are needed with collections containing thousands of items. Journalists requesting photographs of a particular type of event, designers looking for materials with a particular colour or texture, and engineers looking for drawings of a particular type of part, all need some form of access by image content. The existence – and continuing use – of detailed classification schemes such as ICONCLASS [Gordon, 1990] for art images, and the Opitz code [Opitz et al, 1969] for machined parts, reinforces this message.

IV. CONTENT-BASED IMAGE RETRIEVAL (CBIR)

The earliest use of the term content-based image retrieval in the literature seems to have been by Kato [1992], to describe his experiments into automatic retrieval of images from a database by colour and shape feature. The term has since been widely used to describe the process of retrieving desired images from a large collection on the basis of features (such as colour, texture and shape) that can be automatically extracted from the images themselves. The features used for retrieval can be either primitive or semantic, but the extraction process must be predominantly automatic. Retrieval of images by manually-assigned keywords is definitely not CBIR as the term is generally understood – even if the keywords describe image content.

CBIR differs from classical information retrieval in that image databases are essentially unstructured, since digitized images consist purely of arrays of pixel intensities, with no inherent meaning. One of the key issues with any kind of image processing is the need to extract useful information from the raw data (such as recognizing the presence of particular shapes or textures) before any kind of reasoning about the image's contents is possible. Image databases thus differ fundamentally from text databases.

CBIR draws many of its methods from the field of image processing and computer vision. The distinction between mainstream image analysis and CBIR is usually fairly clear-cut. An example may make this clear. Many police forces now use automatic face recognition systems. Such systems may be used in one of two ways. Firstly, the image in front of the camera may be compared with a single individual's database record to verify his or her identity. In this case, only two images are matched, a process few observers would call CBIR. Secondly, the entire database may be searched to find the most closely matching images. This is a genuine example of CBIR.

V. LOCAL BINARY PATTERNS (LBP)

The original LBP operator was introduced by Ojala et al., and was proved a powerful means of texture description. The operator labels the pixels of an image by thresholding a 3 x 3 neighbourhood of each pixel with the centre value and considering the results as a binary number. The 256-bin histogram of the LBP labels computed over a region is used as a texture descriptor. The derived binary numbers called Local Binary Patterns or LBP codes. It codifies local primitives including different types of curved edges, spots, flat areas, etc. Due to its discriminative power and computational simplicity, LBP texture operator [22] has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations.

The most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused by illumination variations. Another important property is its computational simplicity [23], which makes it possible to analyze images in challenging real-time settings. The drawbacks in this system are it is highly sensitive to glasses and it is time consuming process. To overcome the drawbacks of existing system, a new method is proposed i.e. 2D-PCA (Principal Component Analysis). The different machine learning techniques, including Template matching, Support Vector Machines, Linear Discriminant Analysis and the linear programming technique, are used to recognize expressions

VI. CONCLUSION

The LBP methodology has led to significant progress in texture analysis. It is widely used all over the world both in research and applications. Due to its discriminative power and computational simplicity, the method has been very successful in many such computer vision problems which were not earlier even regarded as texture problems, such as face analysis and motion analysis. In texture-based method for background subtraction, each pixel is modeled as a group of adaptive local binary pattern histograms that are calculated over a circular region around the pixel. Other related LBP-based approaches to these problems have been proposed recently. LBP has also been used in many other applications of biometrics, including eye localization, iris recognition, fingerprint recognition, palm print recognition, gait recognition and facial age classification.

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