Review

Image Based Computer Aided Diagnosis System for Cancer Detection

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PII: S0957-4174(15)00098-6
DOI: http://dx.doi.org/10.1016/j.eswa.2015.02.005
Reference: ESWA 9855

To appear in: *Expert Systems with Applications*

Image Based Computer Aided Diagnosis System for Cancer Detection

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Abstract

Cancer is one of the major causes of non-accidental death in human. Early diagnosis of the disease allows clinician to administer suitable treatment, and can improve the patient's survival rate. Traditional diagnosis involves trained clinicians to visually examine the respective medical images for any signs of nodule development in the body. However due to the large scale of the medical image data, this manual diagnosis is often laborious and can be highly subjective due to inter-observer variability. Inspired by the advanced computing technology which is capable of performing complex image processing and machine learning, researches had been carried out in the past few decades to develop computer aided diagnosis (CAD) systems to assist clinicians detecting different forms of cancer. This paper reviews computer vision techniques adopted in medical image analysis, in particular, for cancer detection. The review focused on the detection of the most common form of cancer types, namely breast cancer, prostate cancer, lung cancer and skin cancer. A recent proposed cloud computing frame work has inspired the researchers to utilize the existing works on image based cancer research and develop a more versatile CAD system for detection.

Keywords: Segmentation; Computer vision; CAD system; Breast cancer, Lung cancer; Prostate cancer; Skin cancer; Cancer detection; Computed Tomography (CT); Ultrasound; Mammogram; Dermatography. Visual features,

1. Introduction

Cancer is a type of disease in which a group of cells exhibits irregular cell growth cycle. In the a normal cell cycle, the cells undergo mitosis process to replicate itself and hence the cell grows (Lee and Chen 2013a; Nahar et al 2011); eventually the *programmed cell death* process called apoptosis leads the cells to die in order to regulate its growth. In cancer, the cells lost such balance and grow uncontrollably, to form malignant tumors invading the surrounding tissues. The cancer cell can also migrate to other parts of the body by the bloodstream or lymphatic system, and continue to spread from the new location.

The cause of cancer has not been fully unveiled, however certain habits, such as smoking, exposure to radiations and environmental pollutants are known to cause cancer. Inherited genetic defects are also linked to the cause of some cancers (Nahar et al 2011; Rodrigues et al. 2006; Avila-Garcia et al. 2008; Doi 2005). Early diagnosis of the cancer will allow the clinician to remove the cancer cells via operation or administer suitable treatment plan to eliminate the cancerous cells using chemical or radiation treatment.

Traditionally, cancer can be detected from the presence of certain symptoms, such as irregular markings on the skin, or hard lumps on the body. In clinics, screening tests (Chen and Chen 2006; Pisano et al. 2005; Joshua et al. 2013; Wu et al. 2011) and medical imaging (Nahar et al. 2012; Lee and Chen 2013b; Tang et al 2009; Huang et al 2007; Huang et al 2012) are the initial stages in cancer detection. Once a suspected cancer has been detected, tissue samples from the suspected region are extracted and examined (Nahar et al. 2012; Nahar 2007; Chen and Chen 2006; Hung et al 2011).

Non-invasive diagnosis of cancer involves a trained clinician visually examine different types of medical images, and identify the possible locations which resembles signs of malignant tumors . The accuracy of the diagnosis is highly dependent on the experiences of the clinician. Furthermore, with a large volume of medical database, this process is laborious and hardly consistent (Chen et al. 2007; Cheng et al 2010; Cruz-Roa, et al 2011; Cho et al 2010).

With the advance in digital computing technology, many researchers have combined image processing, pattern recognition, and artificial neural network to develop computer aided diagnosis (CAD) systems to assist the clinicians in the diagnosis process (Rolim et al 2010; Lee and Chen 2013b; Verma & Zako 2001; Ye et al. 2009) Figure 1 shows a general framework for a CAD system for skin cancer detection (Lee and Chen 2013b).

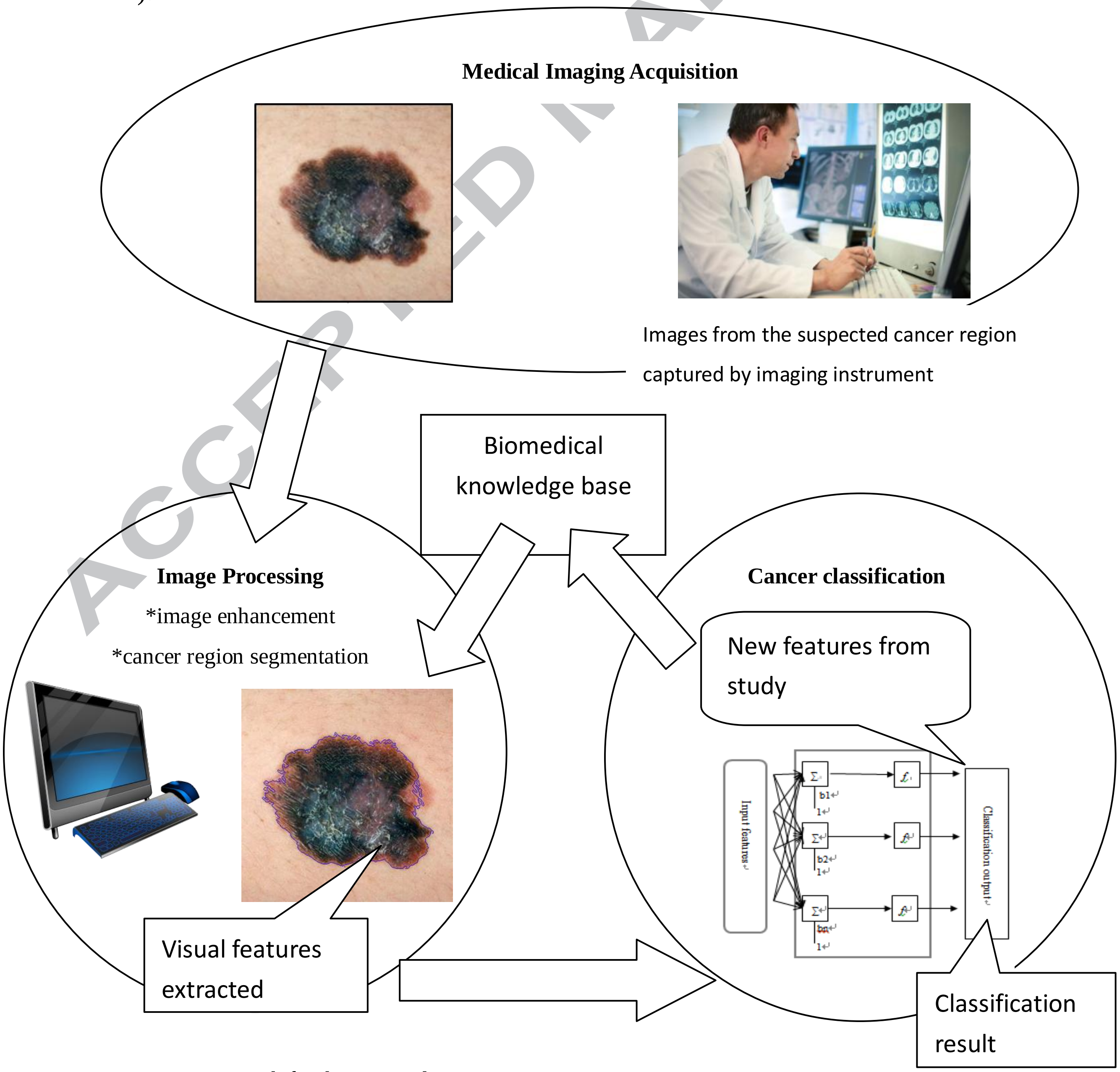


Figure 1 Framework for the cancer diagnosis system

In a CAD system for cancer detection, medical images are recorded using the appropriate imaging systems. The image acquisition device can be adjusted to ensure the consistent image quality under the same laboratory environment (Lee and Chen 2013a; Zheng et al. 2006). The captured images undergo series of software-based algorithms to isolate the suspected cancerous regions from the rest of the image (Lee and Chen 2013; Tong et al. 2010). A biomedical knowledge based features, such as textures (Rodrigues et al. 2006; Tang and Guo 2011), and shapes (Lee and Chen 2013a; Tourassi et al. 2006; Soysal & Chen 2008; Celebi et al. 2005) can be extracted to characterise the extracted segments. This feature space forms a biometric describing the suspected region. A supervised classifier can be implemented and trained using the existing sample images, to learn the distinctive patterns associated with the biometric The diagnosis can be performed by comparing the feature patterns between the test sample and the trained patterns in the classifier features (Lee and Chen 2013; Joshua et al 2013; Sharaf-elDeen, et al. 2013).. Newly developed features from the study can be fed back to the biomedical knowledge database to improve the existing feature sets (Nahar et al 2007; Peng et al 2006).

Image segmentation plays a crucial role in a CAD system. It aims to isolate the suspected region from the rest of the image (Lee and Chen 2013b; Cheng et al 2013). It can also incorporate visual features such as color and texture information with other statistical and biological features to distinguish different regions in an image. Hence the unaffected regions can be removed and leaving the suspected regions which resembles certain visual patterns, such as irregular texture (Padmanabhan and Sundararajan 2012;), color and intensity (Umbaugh et al. 1989; Yuksel & Borlu 2009; Lee and Chen 2013b). An accurate segmentation result will help to determine the location and the size of the tumor, which is important for treatment planning.

The major challenge in this field of research is to build a fully automatic CAD system which can analyze large quantities of images to provide an accurate diagnosis and at the same time, robust enough to handle the biological variations in humans (Spurgeon 2005; Lee and Chen 2013a).

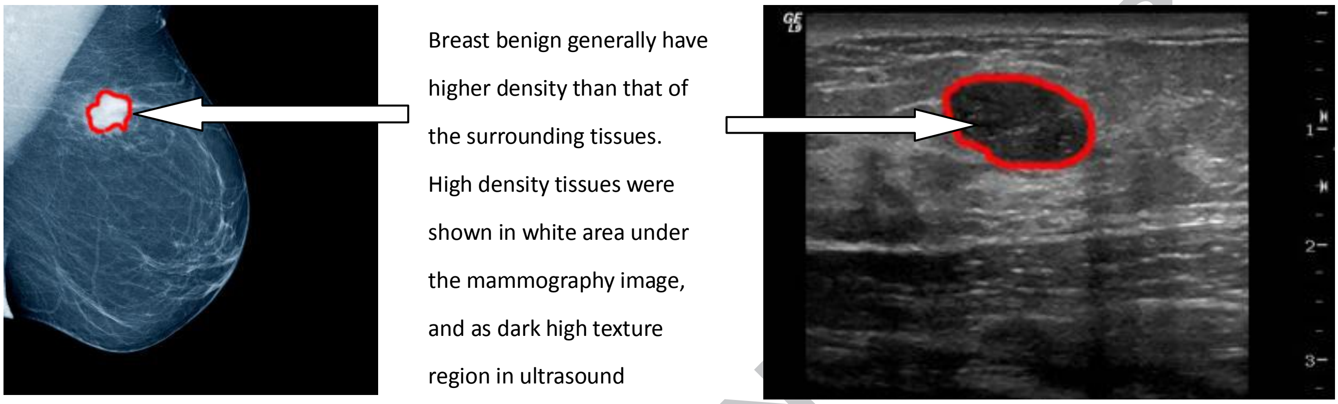
In this paper, we are going to provide an overview of the segmentation process used in these common medical image modalities to detect the most common forms of cancer: breast cancer, prostate cancer, lung cancer and skin cancer. We also investigate the recent work on these cancer detections with medical image processing and analysis. We discuss how image processing techniques have assist the clinicians in IMRT for cancer treatment. To utilize the existing research works on the algorithms to segment and classify for cancer images, a cloud computing frame work for image based cancer research has been proposed. In this paper, we discussed the advantages of this frame work and future works involved in developing a cloud computing based CAD system for cancer research.

2. Breast Cancer Detection

Breast cancer is a type of cancer originating from breast tissue, and it accounts for 23% of all cancers in women (Berman 2007). The most effective way to detect breast cancer is through the breast mammogram screening, however the major limitation for mammography diagnosis is sensitivity. This diagnosis is less sensitive in younger women especially cancers in dense breasts become difficult to detect (Smith et al. 2004;

Baker 2003).

Mammography is the most common imaging technique to detect breast cancer. (Boukerroui et al 2003; Chang et al. 2003; Chen et al. 2002;Cheng et al. 2010). In contrary to x-ray mammography, the conventional B-mode ultrasound is used to distinguish benign masses from malignant cancerous masses. Clinical studies have tried to characterize these masses by the texture and geometric properties (Arger et al. 2001; Huang et al. 2012; Jo et al. 2013). Figure 2 illustrates an example of breast cancer detection in mammography and ultrasound.



a b

Figure 2: Breast cancer image from (a) mammography, and (b) ultrasound: showing the region where a benign has been detected in the breast (indicated with an arrow) – The suspected sighting of the breast benign has shown distinctive features compare to the surrounding normal tissues. (images are adopted from welcome images and Radiologyinfo.org)

A suspected benign can be detected by observing the regions showing abnormal high density. The texture and shape features are commonly used to detect the presence of breast cancer (Baker 2003), however one of the major hurdles in detecting breast cancer in mammography is that the high breast density, usually in young age group, may be difficult to detect the benign in the early stage, when the size is small. In conjunction with mammography, ultrasound technique has also been used to detect the presence of the benign in breast.

Recently, intensity-modulated radiation therapy (IMRT) has been applied for the treatment of breast cancer (Hoppe et al. 2012; Popescu et al 2010). Clinical studies have shown improvement on dose distribution throughout the breast, and minimize the acute skin reactions for the patients (Popescu et al 2010). However, this treatment has not been widely administered in some clinic institutes because the treatment involving CT scan to be performed for each patient, and target volume need to be delineated, all these are time consuming and laborious (Hurkmans et al. 2001). The treatment will involve will require daily expose to the radiation dose for the treatment period. This may increase the risk of damaging the surrounding tissues and developing secondary cancer. Despite the effectiveness in dose distribution, the survival rate for IMRT compare to non-IMRT techniques remains an open question (Hoppe et al 2012; Arger et al 2001).

2.1 X-ray mammograms

In the image-based CAD for breast cancer, there are two different goals in segmentation of micro-calcifications: to obtain the locations of the suspicious areas to assist clinician for diagnose; and to classify the abnormalities into benign or malignant, which is a cancerous mass (Baker 2003; Berman 2007;

Cheng et al. 2010). The major types of image segmentation process commonly used in the CAD for breast cancer are: *low level thresholding; region based techniques; Mathematical morphology* and *texture based segmentation*.

2.1.1 Low level thresholding

Low level thresholding technique utilized the low level image information such as local pixel values embedded in the mammogram images to segment images into different regions. This technique is based on the expected bimodal intensity distribution in the selected window which contains the sub-images to be segmented. (Baker 2003; Ayres & Rangayyan 2007; Berman 2007) This approach does not require prior information for the thresholding based on the image intensity. However the lack of spatial characteristics means it is not effective to images with high noise.

2.1.2 Region based approach:

Region growing is a common method of segmentation. It groups the near-by pixels with the properties similar to those of a seed pixel. Muralidhar et al. (2010) used a model based active contour approach to delineating breast cancer. Baker (2003) and Burhenne et al. (2000) described and compared local thresholding and region growing methods, and had shown that local thesholding has greater stability but is more dependent on parameter selection. However the region based process requires image with high contrast and require initial seeds. The process can be time consuming.

2.1.3 Mathematical morphology:

Edge detection is a traditional method for segmentation. Many operators such as Gabor operators, Sobel gradient, Prewitt gradient and Laplacian operator have been developed to determine closed edge in image (Zheng 2010), and hence delineate the image into regions. Other mathematical morphological operations such as erosion, top-hat transformation and complex morphological filters with multi-structure elements can also be used with adaptive neuro-fuzzy inference classification techniques (Huang et al. 2012). This method is generally efficient for analyzing geometric aspect of the image. However it generally requires a priori knowledge of the resolution level of mammograms in order to determine the sizes and shapes of the structure elements.

2.1.4 Texture-based segmentation

Image texture analysis has also been used in CAD system for feature enhancement, segmentation and classification. Texture features such as multi-resolution wavelet features (Chen et al. 2002; Mencattini et al. 2008), or Gabor features (Jo et. al. 2013, Zheng 2010) can be utilized to distinguish the micro-calcifications (small object) and normal tissues (large objects). The multi-resolution wavelet representation provides a natural hierarchy to embed an interactive paradigm for accomplishing scale-space feature analysis. The common scheme for wavelet transform on the detection of micro-calcification is to reconstruct the image from the transform coefficients modified at each level by local and global non-linear operators (Mencattini et al. 2008). Jo et al. (2013) has proposed a breast cancer detection algorithm based on the texture properties of the mass area. They measure the homogeneity using support vector machine to analyze the texture properties of the selected mass area. Zheng (2010) developed the Gabor Cancer Detection (GCD) algorithm, with utilized Gabor features. A set of edge histogram descriptor are extracted as texture descriptor for analysis. To achieve maximum performance, it is important to study two crucial issues: wavelet base and non-linear functions of the wavelet coefficients.

2.2 Ultrasound imaging

Ultrasound is a non-invasive and mobile medical image modality to detect masses in the breast. Ultrasound imaging of the breast is typically done as an addition to x-ray mammography when breast cancer is suspected. These masses can be classified into benign masses and malignant masses by study their texture and geometric properties (Arger et al. 2001; Boukerroui et. al. 2007; Horsch et al. 2006). Inspired by these studies, researchers are seeking for an image-driven CAD system for automatic detection and characterization of breast cancer.

(Horsch et al 2004, 2006) has presented a method using threshold technique on the images with pre-enhanced mass structures. They determined and compared the effectiveness of various features using linear discriminant analysis, (Horsch et al. 2006; Drukker et al. 2013) and found the best two features, namely, depth-to-width ration (shape), and normalized radial gradient (margin), to distinguish benign and malignant masses.

Huang and Chen (2004) proposed a combination of neural network classification and watershed segmentation methods to extract the contours of the breast tumor in ultrasound image. In this approach, a self-organizing map (SOM) texture-based neural network is used to adaptively select appropriate preprocessing filters, which improves the effectiveness of the watershed segmentation algorithm. Madabhushi and Metaxas (2003) combined intensity, texture information, and empirical knowledge adopted by the clinicians with a deformable shape model and has automated the segmentation process, despite training is a prerequisite. Table 1 outlines the comparisons of these segmentation techniques for breast cancer detection, the image modalities used for these algorithms and related works.

2.3 Intensity-modulated radiation theropy (IMRT)

Radiotherapy is an effective treatment modality for early stage breast cancer. Despite the apparent success from multiple of clinical studies (Hoppe et al 2012), other studies also demonstrate significant dose inhomogeneity in the superior and inferior regions of the breast when applying wadged beam in the conventional treatment (Buchholz et al. 1997; Senkus-Konefka & Jessem 2007). Therefore it is important that an optimum solution for whole-breast radiotherapy should improve on dose homogeneity.

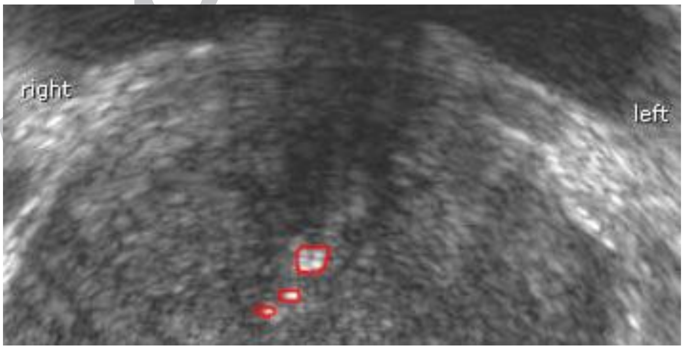
The role of IMRT is well established due to its tumor doses escalation characteristics. The goal is to deliver high dosage of radiation to the tumor while sparing the surrounding tissues to minimize damages to the normal tissues. Although there are limited literature describing image processing and segmentation used in this modality, especially for breast cancer treatment. It is evident that to perform an accurate diagnosis and treatment for IMRT, a precise model of the anatomical structure and the location of the tumor need to be constructed. Studies have shown the long term side effects of the IMRT treatment for breast cancer to the surrounding tissues and organs (Senkus-Konefka & Jessem 2007; Hoppe et al. 2012) Furthermore, due to the slow rotation of the IMRT system, motion artifacts have become apparent in the IMRT imaging, and may affect the precision of the treatment.

Segmentation techniques	algorithms	Image motility
Statistical method using thresholding: Use global low level features or local statistic information	Geometric constrained phase model (*Ayres & Rangayyan 2007)* Support vector machine for intensity features (Chang, 2003) Multi-resolution analysis (Nakayama et al. 2007)	mammography
Region based approach:	3D region grow technique (Horsch et al. 2004) Watershed algorithm (Huang & Chen 2004)	ultrasound
Mathematical morphology:	Model based active contour (*Muralidhar et al. 2010*) 3D discrete active contour (Chang, et al. 2003)	mammography; ultrasound
Texture-based segmentation:	Dynamic wavelet processing (Mencattini et al. 2008) Wavelet transform & neural network (Chen et al. 2002) Gabor operator for breast density pattern (Kinoshita, et al. 2007) Gabor filters (Zheng, 2010)	mammography ultrasound

Table 1: Comparison of segmentation methods for breast cancer detection

3. Prostate Cancer Detection

Prostate cancer is the most commonly diagnosed cancer in adult male populations. Early detection and intervention of progressive prostate cancer may help to improve the survival rate (Lim et al. 2008; Hricak et al. 2007). The key to the diagnosis, treatment and monitoring of this disease depends on the accurate segmentation of the prostate volumes and boundaries. Ultrasound has been the main imaging modality for prostate related applications because it is cost effective, innocuous and can be monitored in real time (Bloch et al. 2007; Campadelli, et al. 2010; Sung et al. 2011). However the major short coming of this image modality is its low signal-to-noise ratio and the presence of speckle noise make it difficult for automatic segmentation of the ultrasound images (Sung et al 2011; Vos et al. 2008; Hricak et al. 2007; Lim et al. 2008). Figure 3 depict the prostate cancer nodules in an ultrasound image.



The prostate nodules are generally small, and in ultrasound imaging, these nodules are difficult to detect due to high level of speckle noise present in ultrasound images.

Figure 3: Prostate cancer image from ultrasound: indicating in red, showing the region where small cancerous nodules have formed in the prostate region (image adopted from Radiologyinfo.org)

Classical techniques have been proposed for prostate segmentation. Sung et al. (2011) used the baseline and peak intensities of the image signal in conjunction with other perfusion parameters to determine the size of prostate cancer using a supported vector machine. Derivative edge detection techniques and non-linear filtering (minimum/maximum filtering) techniques were also introduced in (Heijmink et al. 2007), to obtain the second derivative and the gradient images which represent the possible edges of the prostate. However these methods have not used shape modeling and have undergone limited validation.

Secondary features have also been used in detecting prostate boundary. Statistical moments have been taken into account for nature of TRUS image by considering the probe position in the shape normalization step and by making the image feature descriptor invariant to probe rotation (Choi et al. 2007; Doi 2005). Liu et al. (2009) proposed an unsupervised segmentation method, using fuzzy Markov random fields for the segmentation of multispectral MR prostate images. In their study, both hard and fuzzy MRF models have two groups of parameters to be estimated: the MRF parameters and class parameters for each pixel in the image. Manaco et al. (2010) used probabilistic pairwise Markov models to detect regions of carcinoma in the prostate region.

Recent research has focused on the including prior information about shape and speckle models, and delineate prostate in for 3D guided biopsy for prostate cancer. Fei et al. (2011) developed an automatic segmentation method based wavelet transform for 3D TRUS images of the prostate, and also developed a non-rigid registration algorithm for TRUS and PET/CT images. Yin et al. (2012), developed an automated CG segmentation algorithm based on Layered Optimal Graph Image Segmentation of Multiple Objects and Surfaces (LOGISMOS). 3D segmentation and registration on the prostate regions allows the CAD to automatically detect the boundary of the prostate region and accurately guide the biopsy system to the target region. Table 2 shows the recent work on prostate cancer detection algorithm and the corresponding prostate cancer image modalities

Detection techniques and algorithms	Prostate cancer image modalities
SVM with pixel intensity in conjunction with perfusion parameters (Sung, et al. 2011)	TRUS
Derivative edge detection and non-linear filtering (Heijmink et al. 2007)	TRUS
Fuzzy Markov random fields (Liu et al. 2009)	MRI
Probabilistic pairwise Markov models (Manaco et al. 2010)	MRI
Shape and speckle model using wavelet transform (Fei et al. 2011)	3D TRUS, TRUS and PET/CT
LOGISMOS for segmentation and registration (Yin et al. 2012)	3D MRI

Table 2: Recent works on prostate cancer detection algorithms.

4. Lung Cancer Detection

Computed tomography (CT) is the most sensitive and specific diagnostic modality for detecting lung nodules. The reliable detection of such nodules is crucial for early detection of lung cancer and other nodular lung diseases. (Chien et al. 2008; Oh, et al. 2011; Wu et al. 2011) Automatic detection of lung nodules is the most study problem in computer analysis of chest radiographs. Nodules show up as relatively low-contrast white circular objects within the lung fields, and are difficult to detect due to overlapping shadows from other structures such as vessels and ribs (Wu et al. 2011; Ye et al. 2009). Figure 4 illustrates an example of the lung cancer detection in X-ray and chest CT images.

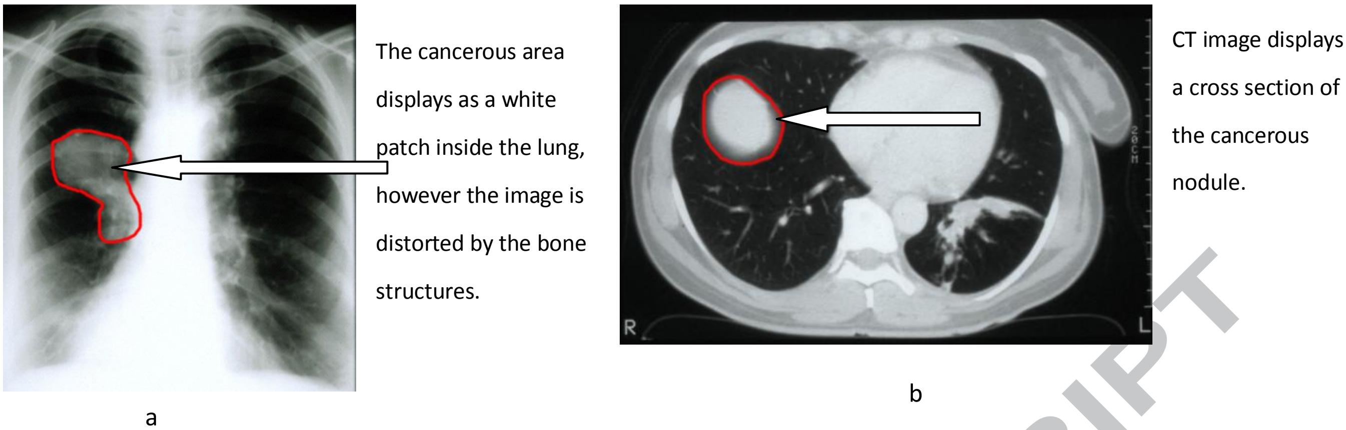


Figure 4: Lung cancer image from (a) X-ray, and (b) CT imaging: showing the region where cancer (indicated with an arrow) has been formed in lung. (images adopted from welcome images)

In chest x-ray image, the cancer region has been shown as a massive white region in the lung area. Typical feature used to detect lung cancer in X-ray is the image illumination, and the size of the effected region. However, the major issue facing in lung cancer segmentation in X-ray imaging is that the overlapping of the ribcage makes the lung nodules, an early form of lung cancer, difficult to detect (Tanino, et al. 2003) Chest CT images, on the other hand, displays the horizontal slides of the lung to detect the presence of the lung nodules developed in the lung (figure 4b). The CT image offers the clear image quality without overlapping distortion as shown in the chest X-ray. However the presence of air packets in the lungs can cause errors in lung nodule detection (Li, 2007). Automatic detection of lung nodules consists of two steps: 1) initial candidate nodules detection and 2) false positive reduction (Li, 2007).

4.1 Nodule candidate detection

Several methods applied filters to enhance the nodules or eliminate background by blurring (Zhao et al. 2004; Linguraru et al. 2006). Nodule candidates are detected using template marching or a modified Hough transform (Tanino et al. 2003; Ye et al 2009). In other cases the nodule is detected by thresholding techniques (Ko and Betke 2001; Zhao et al. 2004). These methods utilise the global intensity information to identify the lung nodules, however they requires images with high contrast and are vulnerable to image distortions. Boyce et al. (2013) investigated the lung nodule detection with the use of stereoscopic visualization compared with the standard posero-anterior images. Their preliminary result has shown that the use of stereoscopic visualization reduced the sensitivity for nodule detection, however it improved the positive predictive value.

4.2 Reduction of false positives

A related problem is to classify nodules into benign or malignant. Supervised learning scheme has been commonly used in classification and reduces FPs. Clinically identified samples have been used to determine benign and malignant nodules by evaluating the correlation between the test images and nodule samples (Oh et al 2011; Samei et al. 2007; Ye, et al. 2009; Ge et al. 2010). They had performed an impressive result but such CAD systems require massive training and learning. Classifiers such as nearest neighbor (Tanino et al. 2003; Zhao et al. 2004) require human interaction to initiate the clusters. Table 3 outlines the common classification scheme used for classifying lung nodules.

Classification scheme	Algorithms used	Image motilities
Supervised Learning	Bayesian network (Oh, et al. 2011) 3D gradient field and 3D ellipsoid fitting (Ge, et al. 2010) SVM (Ye, et al 2009)	X-ray CT 3D-CT,
Clustering	VNQ filters and PCS-based classification (Tanino et al. 2003) LDM algorithm (Zhao, et al. 2004)	3CT

Table 3: Common classification schemes for lung nodule classification

4.3 IMRT in lung cancer treatment

The application of IMRT in lung cancer treatment is a relatively new procedure. The effectiveness of this procedure lies heavily on the accurate target volume delineation. Inaccurate target delineation can compromise the treatment outcome and may also damage the surrounding normal lung tissue, and other critical organs. An approach based on FDG-PET techniques for guided IMRT had been introduced by Song et al. (2006). This technique use both CT and PET/CT images to construct the cross section of the lung and isolate the tumor location. The preliminary result shows improvement on target volume delineation.

5 Skin Cancer Detection

Skin cancers can be classified into malenoma and non-malenoma. Although melanomas are much less common, they account for most of the mortality from skin cancer. Detection of malignant melanoma in its early stages considerably reduces morbidity and mortality (Carrara et al. 2007; Lee & Chen 2013a). Dermatoscopy is a non-invasive imaging technique based on oil immersion, which renders the skin translucent, hence allowing, and therefore offers clear visualization of surface and subsurface structures. However to automatic segment a skin image into lesions is a challenge task. Figure 5 presents typical dermatoscopy images for skin cancer detection.

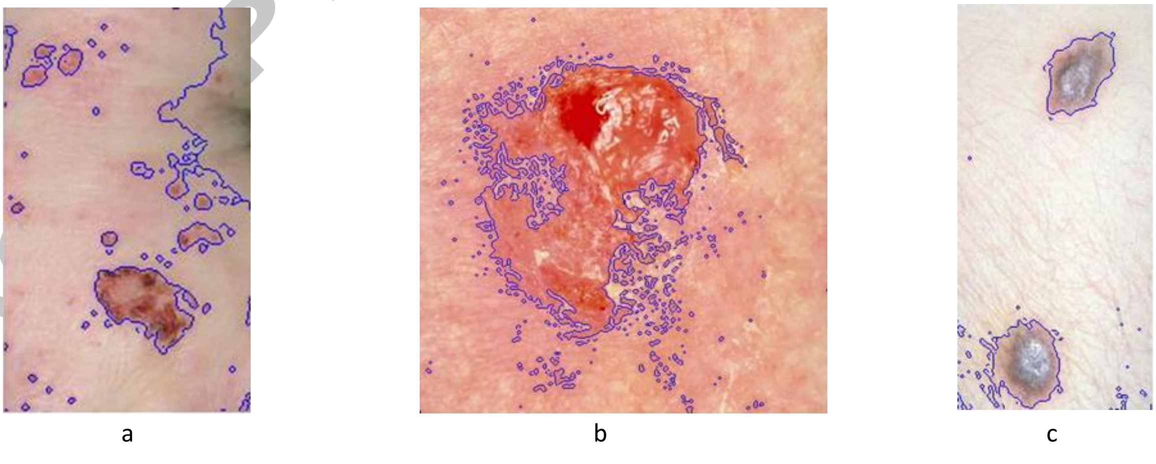


Figure 5: Skin dermatoscopy images for (a) Squamous cell carcinoma; (b) Basal cell carcinoma and (c) Malignant melanoma. These three types of skin cancer display different visual characteristics.

The squamous cell carcinoma (Figure 5a) and basal cell carcinoma (Figure 5b) are the most common forms of skin cancer. The squamous cell carcinoma is commonly a red, thickened patch at the sun-exposed skin, this skin cancer type usually effecting a larger area of the skin. Basal cell carcinoma, on the other hand, usually presents as a raised, smooth bump on the skin. However the most lethal form of skin cancer is malignant melanoma, (Figure 5c) it appears in dark colour and usually in the irregular shapes (Lee and Chen 2013b) .

5.1 Skin cancer segmentation

The changes in the pigment of the skin have been the key features to detect skin cancer. However the quality of the skin dermatography is highly influenced by the environment, such as lighting and instrument. Uneven lightings may cause the shadows and uneven illumination on the skin, and cause error in segmentation. Furthermore, segmentation with based only on the color features may not be robust to address the variations in nature skin colors. Other features such as asymmetry, border irregularity, and area are also used in clinical diagnosis. Researches have been conducted to combine these clinical features to detect skin cancer automatically (Carrara et al. 2007).

5.2 Recent works in automatic skin cancer image extraction

Celebi et al. (2005) combined color quantization and region growing method to segment skin lesions under the unsupervised learning algorithm to detect the border of the infected skin cancer. Carrara et al. (2007) investigated the use texture information embedded in the image with a supervised learning algorithm to assist clinicians to detect skin cancer with varying skin pigments These approaches are less dependent on the color information of the dermatoscopy images, and can address the limitation of the color clustering based approaches, such as the similar color tones of the hair and the lesions.. Despite the color features embedded in the skin images, edge detection algorithm which uses the texture variations between the normal and cancerous skin regions has also been investigated (Tang and Guo, 2011). Lee and Chen (2013b) used the color constancy approach to address the color tone variations due to different skin samples and image capturing environment. Using the type-2 fuzzy set algorithm to determine an optimum threshold level, this approach also allow to segment three common types of skin cancer, namely basal cell carcinoma, squamous cell carcinoma and malignant melanoma. Comparisons of the recent works on skin cancer segmentation has been summarized in Table 4.

Recent works	Features used	Algorithm	cancer detection
Celebi et al. 2005	HSV color,	Color quantization Region growing	Malignant melanoma
Carrara et al. 2007	RGB color, texture	Supervised ANN Gabor filters	Malignant melanoma Squamous cell carcinoma
Tang & Guo, 2011	Color, texture	Wavelet diffusion, active contour	Malignant melanoma
Lee & Chen, 2013b	RGB color	Optimum threshold using type-2 Fuzzy set	Basel cell carcinoma Squamous cell carcinoma Malignant melanoma

Table 4: Recent work in skin cancer segmentation algorithms

6 Future research directions in CAD for cancer detection

The image processing based CAD for cancer diagnosis has only been made to detect singular cancer type. Research in image processing for cancer segmentation had utilized the low level features embedded in the image to detect the presence of cancer cell. Depending on the image modality used, multiple visual features usually used in conjunction with some optimum classification algorithm to obtain the best segmentation result.

6.1 Image features in cancer segmentation

As discussed in the previous sections, cancer images from different modalities had provided different image characteristics to distinguish cancerous regions from the normal tissue. In automatic cancer image segmentation, low level image features have been widely used to represent these visual differences in the cancerous region.

In X-ray imaging modalities, such as mammography and chest X-ray, the density of the body tissue is shown in high intensity. Detection on the cancerous cells in breast and lung in X-ray can be influenced by the density of the body tissue. In ultrasound imaging technique, the texture and density of the body tissue can be detected by the resonance of the sound wave. These images generally display the shape of the organs or tumours. However ultrasound generally have poor image quality, precise boundary of the cancerous region always difficult to obtain, and it is difficult ti identify small nodules. Computer tomography (CT) takes series of images showing horizontal slides of the region. The image quality displays the shape and density of the organ tissues. Image intensities and shapes are the common features used to detect cancerous region in this modality. Skin cancer images are obtained by dermatography, which displays the full colour information about the skin pigment. Cancerous regions are detected based on the colour variations. Table 5 summarised the features used in different image modalities and the targeting cancer type detection

Image modality	Image features	Cancer types	Major issues
X-ray	intensity, texture	breast; lung	highly affected by tissue density and overlapping organs and bone structure
Ultrasound	texture, shape	breast; prostate	difficult to detect small nodules and accurate border of the tumour
Computer tomography	intensity, shape; texture	lung; prostate	sensitive to other structure in the organ, such as blood vessels and air packets in lungs.
Dermatography	colour, shape	skin	highly affected by the skin tone variations and ambient light source.

Table 5: Comparison of cancer imaging modalities for different cancer detection.

In addition, semantic features such as texture pattern definition, the size of the region, and shape definition can provide extra biological characteristics in segmentation. These semantic features have been used to identify or track particular object in multimedia data (Tjondronegoro & Chen 2010), and can also provide key features in cancer segmentation.

Multiple modalities analysis have also been deployed in medical practice to detect cancer (Horsch et al 2006). However in the CAD for cancer detection, it only utilise single diagnosis from single modality, and sometimes the result may be contradictory. Extension for image processing in cancer detection, can combine critical features extracted from images in different modality to improve the detection of cancer in terms of its location, size and shape.

6.2 Cloud computing in CAD design for cancer detection

A cloud computing framework design for cancer research has been proposed based on the Microsoft cloud service technology, (Avila-Garcia, et. al. 2008) to utilize the massive existing algorithms developed by different researchers. Figure 6 shows the proposed cloud computing frame work for image-based cancer detection.

In cloud computing, the image database and the existing image processing algorithms are made available upon the user queries (Rolim et. al. 2010, Vecchiola et. al. 2009). This allows the clinicians to access the most suitable algorithm to process the data image according to different cancer type and different image modalities that were captured. Clinicians can access and update the new findings in cancer research, such as new features to detect cancer. The access to different image database allows the clinicians to consult with different case studies or collaborate with other researchers of the same field. In technical aspect, this frame work saves the time and resources of implementing pre-existing algorithms for analyzing different image data. New image data captured using new devices can be made available for all researchers and make the development of new algorithms more efficient.

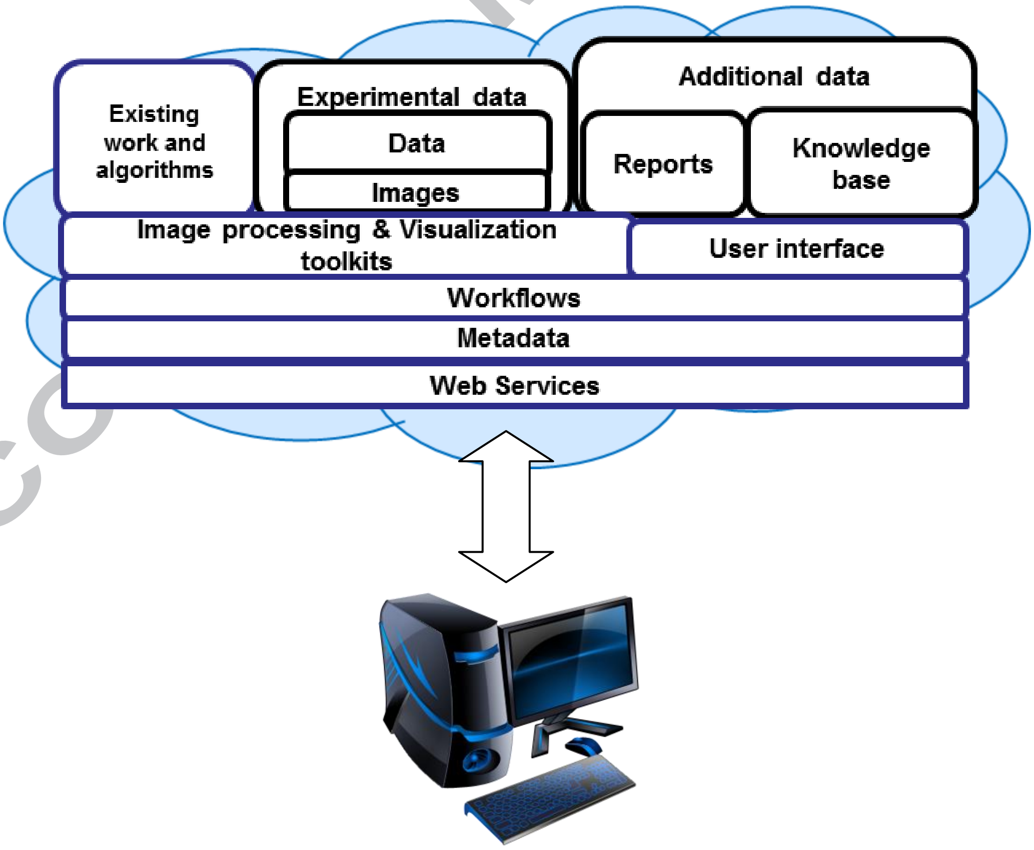


Figure 6: Cloud computing framework for image-based cancer detection. (adopted from Avila-Garcia, et. al. 2008)

The challenge in developing such framework include building a repository for the existing algorithms; developing an effective metadata information for cancer images; define the work flow for accessing sensitive medical data (Avila-Gacia et al. 2008, He et al 2010).

7 Conclusion

In this survey of image based CAD system for cancer detection, we had studied the major image modalities for detecting different cancer types in the medical field. We compared different segmentation algorithms for delineating different cancerous region, and outlined the advantages and disadvantages in each segmentation algorithms. To correctly identifying the cancer cell, relevant features are extracted and studied. In this paper, we examined the major visual features used to detect the four major types of cancer, namely, breast cancer, lung cancer, prostate cancer and skin cancer. In this paper, we also discussed and compared the recent studies in image based cancer segmentation and detection algorithms. The visual features comparison for different cancer types and the corresponding medical image modalities for cancer detection allow the researchers to compare the characteristics of different cancers and the existing image processing approaches in cancer detection.

Image segmentation had proved to be very effective in detecting cancerous tumors in different medical imaging modalities, however due to variations of biological information on different parts of the human anatomy, human intervention is almost inevitable. It requires experienced clinician to either provide training data, or set up the initial conditions for classification. Researches have been done to detect different types of cancer based on the visual information extracted from medical images. However most of the image based cancer diagnosis systems only detect singular type of cancer, and most image processing algorithms are customized to address particular set of image data, or images from the same modality. Recently a cloud computing framework has been proposed to incorporate algorithms developed by different researchers for cancer image detection. The framework will encourage the researcher to collaborate with clinicians to develop a versatile CAD system for cancer research. This cloud computing frame work can be served as the repositories for the existing image processing algorithms and cancer image databases. Providing a research and development platform for image based cancer research. This extension allows the future CAD design to be more versatile, and the newly discovered information can be shared more rapidly. The future extension in cloud based CAD design requires researchers to build a biomedical visual feature archive and algorithm archive that allows the cloud based CAD to utilize the existing algorithms and feature sets for cancer detection, and allows the newly developed algorithms, features and biological information to be updated. Another future extension for cancer detection is to use multiple image modalities for cancer study. Different types of image modalities offer different insights of the cancer region. A combination of the feature analysis from these features can improve the effectiveness and accuracy for cancer detection.

Another future research direction for image based cancer detection can incorporate biometrics of the individual patient, allows a customized medical diagnosis and treatment for cancer. Biometric information such as the size and thickness of the organs and tissues can help identify the exact location of the internal cancerous cells such as lung and breast carcinoma, and allows proper radiation dosage delivered to the cancerous site and minimizes the damages to the surrounding normal tissues. Natural skin tone of the individual patient can be used to accurately delineate the boundary of skin cancer. Allows the clinicians to determine the types of skin cancer, and monitor its propagation on the skin surface.

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Hightlights:

1. Studies and compare the recent works in different types of cancer detection
2. Low level features comparison for detecting different cancer types
3. Compare image modalities and associated segmentation algorithms
4. Research extension discussion in intermediate feature analysis and cloud structure for cancer detection