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Framework using Diagnosis and CBIR System for Identifying Contrast Agent Concentration

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Abstract: Detection of cancerous cells is one of the conventional problems in medical image processing. Although there were many attempts to perform an investigation and come out with an efficient framework that ensures somewhat reliable detection. However, very few studies have focused on detecting the contrast agent exclusively in prostate cancer. Identifying the contrast agent precisely can assist the physician to perform correct diagnosis of the patient suffering from prostate cancer and thereby it becomes possible for the physician to recommend correct treatment. In this paper, we propose a framework that takes the input of a radiological image and perform adaptive complex independent component analysis (ACICA), reference region (RR- based method) and Pharmacokinetic modeling (PK-Modeling) for highlighting the effective intravascular contrast concentration agent. The system is rendered more precise by incorporating CBIR system using visual descriptor.

Keywords: Independent component Analysis, reference region-based method, Pharmacokinetic modeling, Prostate Cancer, CBIR

1. Introduction

Prostate cancer is the second most frequently diagnosed cancer and is the disease that causes the sixth leading cancer death in males. Cancer begins to grow in the prostate - a gland in the male reproductive system. The prostate cancer starts in the gland cells - this is called adeno-carcinoma. Prostate cancer is mostly a very slow progressing disease. But sometime it grows aggressively and the cancer cells may spread from the prostate to other parts of the body, particularly the bones and lymph nodes. The prostate is an exocrine gland of the male reproductive system, and exists directly under the bladder, in front of the rectum. An exocrine gland is one whose secretions end up outside the body for e.g. prostate gland and sweat glands. It is approximately the size of a walnut. In previous work, a method is proposed based on an adaptive complex independent components analysis (ACICA). This method is used to calculate the intravascular concentration in the tissue of interest. This method provides a good estimate to intravascular signal both temporally and spatially. But, due to the partial volume effect, it's unable to find the true amplitude of the concentration curve in the early phases of the bolus passage and also affect the PK parameters. The other method proposed by Fan et al, which is called as a reference region based method use to correct AIF due to its under-estimation of the early phases. But this method required knowledge of the contrast agent in an artery. It also needs optimization for the time lag between the arrivals of bolus in the region. Medical images are usually fused, subject to high inconsistency and composed of different minor structures. So it requires the efficient retrieval technique. However, the drawbacks of the existing system are:

- In ACICA method, the contrast uptake in an artery is unable to measure the contrast concentration in the early phases (it under-estimates the peak) and fails to capture the profile of the intravascular curve (its shape is different from that of the prostate) and this effects the PK parameters.
- The RR-based method requires knowledge of the contrast agent in artery for correction of AIF (arterial input function/PK parameters) for the under-estimation in the early phases.
- Contrast uptake in an artery is needed to finding the time lag between the contrast agent arrival in the artery and its arrival in the tissue of interest. This additional parameter makes the system more complex, difficult to solve and finally subjected to error. The image is probably one of the most important tools in medicine .Usually the medical images are fused, subject to high inconsistency and composed of different minor structures.
- The PK-modeling applied on corrected concentration curve provide high K^{trans} value on few regions of the prostate, indicating it is suspicious and corresponds to tumor and thereby reduces the large number of false positives.
- Hard-copy image formats are becoming rarer. Maintenance, storage room and the amount of material to display images in this format contributed for its disuse. Curiously, this transition from hard-copy to soft-copy images is still the focus of an interesting debate related with human perception and interpretation issues during exam analysis.

This ACICA algorithm calculate the intravascular components and convert the intravascular signal into intravascular contrast concentration curve (AIF) which was under-estimated in the early phases of the bolus passage of the contrast agent through tumor (prostate) vasculature because the proposed algorithm is provided with DCE-MRI data. Then RR-based Method use to correct AIF due to its under-estimation of the early phases, since it does not need the knowledge of the contrast uptake in an artery which is outside the tumor. The pharmacokinetic analysis (PK-analysis) is applied on corrected intravascular concentration curve. Using CBIR technique the various MR image databases is created. The results are applied to the database of MR images and checks for the similarity matching value and finally retrieve the required image.

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2. Related Work

Mehrabian et al., [1] presented an adaptive complex independent component analysis method is developed to identify and separate AIF from complex Dynamic Contrast Enhanced-MRI (DCE-MRI) data. The results are compared with a previously introduced AIF estimation method that applied ICA to magnitude DCE-MRI data. Using simulation and experimental phantom studies it is shown that using both magnitude and phase data (complex) results in a more robust and more accurate AIF measurement algorithm.

Mehrabian et al., [2] studied a method is introduced to calculate the intravascular concentration in the prostate tissue using an adaptive complex independent components analysis (ACICA) method and to correct this curve for the early phases of the passage of the contrast agent through tumor vasculature. The results are applied to DCE-MR images of the prostate of a 70 year old prostate cancer patient and the calculated map is examined using tumor location defined by multi-parametric MRI.

Fan and Karczmar [3] purposed of this research was to develop a novel numerical procedure to deconvolute arterial input function from contrast concentration vs. time curves and to obtain the impulse response functions from dynamic contrast enhanced MRI data. Numerical simulations were performed to study variations of contrast concentration vs. time curves and the corresponding impulse response functions.

Sintra [4] have depended on a contrast function that serves as a rotation selection criterion. One of the contrasts proposed is built from the mutual information of standardized observations. For practical purposes this contrast is approximated by the Edge worth expansion of the mutual information, and consists of a combination of third- and fourth-order marginal cumulates.

Hyvärinen et al., [5] proposed that this residual dependence structure could be used to define a topographic order for the components. In particular, a distance between two components could be defined using their higher-order correlations, and this distance could be used to create a topographic representation. Thus they obtain a linear decomposition into approximately independent components, where the dependence of two components is approximated by the proximity of the components in the topographic representation.

Ganesh et al., [6] introduced the fundamentals of BSS and ICA. The mathematical framework of the source mixing problem that BSS/ICA addresses was examined in some detail, as was the general approach to solving BSS/ICA. As part of this discussion, some inherent ambiguities of the BSS/ICA framework were examined as well as the two important preprocessing steps of centering and whitening. Specific details of the approach to solving the mixing problem were presented and two important ICA algorithms were discussed in detail. Finally, the application domains of this novel technique are presented. Some of the futuristic works on ICA techniques, which need further investigation are discussed.

Ahmad and Ghanbari [7] reviewed independent component analysis (ICA) technique based on Kurtosis contrast function. They briefly present the common independent component analysis algorithms that use Kurtosis as a criterion for non-Gaussian. Based on the literatures, they compare these algorithms in terms of performance and advantages.

Kolenda and Hansen [8] analyzed the feasibility of independent component analysis (ICA) for dimensional reduction and representation of word histograms. The analysis is carried out in a likelihood framework which allows estimates of the loadings (source signals), the mixing matrix and the noise level. In the face of noisy signals, the estimated sources are non-linear functional of the observed signals, in contrast to the linear noise free case. They also discuss the generalizability of the estimated models and show that an empirical test error estimate may be used to optimize model dimensionality, in particular the optimal number of sources.

Sararu et al., [9] described a new classification methodology based on the use of Independent Component Analysis and Wavelet decomposition (ICAW) techniques. An ensemble system of classifiers is built such that each classifier independently decides the assignation of the test examples on several representations resulted by taking projections computed by wavelets and Independent Component Analysis (ICA).

Chen et al., [10] present a realistic and fast method, GHICA, which overcomes the limitations in multivariate risk analysis. The idea is to first retrieve independent components (ICs) out of the observed high-dimensional time series and then individually and adaptively fit the resulting ICs in the generalized hyperbolic (GH) distributional framework. For the volatility estimation of each IC, the local exponential smoothing technique is used to achieve the best possible accuracy of estimation. Finally, the fast Fourier transformation technique is used to approximate the density of the portfolio returns.

3. Proposed system

Basically, the proposed system discusses about a method for evaluating the intravascular concentration in the prostate tissue called as adaptive complex independent components analysis method. Finally, CBIR techniques based on clustering will be used for this purpose. The proposed product using Content-based image retrieval (CBIR) aims at finding images of interest from a large image database using the visual content of the images. The user must specify the proper input parameters.

- The user must have the in-depth knowledge about the formulation of independent component analysis and later the enhanced part of it termed as adaptive complex independent components analysis.
- The user should adopt the development skills over Matlab development environment and should be aware of image processing functions and methods.
- The user should understand the clustering mechanism in CBIR techniques for carrying out effective disease classification.

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3.1. Functional Requirements

Functional Requirement defines a function of a software system and how the system must behave when presented with specific inputs or conditions. These may include the calculations, data manipulation, processing and other specific functionality. The following are the functional requirements.

- The input image must be subjected to dynamic contrast enhancement.
- The system must implement adaptive complex independent components analysis for better classification.
- The system must apply reference region based approach.
- The system may use visual descriptors.
- The system should use clustering technique to carry out CBIR technique.

The architecture of the proposed method is as shown below in Figure 1. Figure 1 highlights the architecture of the proposed work that is targeted to be accomplished. The architecture shows that mainly the operations are carried out in preprocessing the input MRI image of prostate cancer which is subjected to new technique of ICA (Independent Component Analysis) called as Adaptive Complex Analysis to basically extract the information pertaining to intravascular contrast agent concentration. The independent components are extracted from the models and stored in matrix, which is then subjected to RR-based method, PK-Modeling and finally subjected to Content Based Image Retrieval (CBIR) system. The project is based on the base paper "Using Independent Components Analysis to calculate intravascular contrast agent concentration in prostate cancer" by Mehrabian et al. However, as a contribution, the proposed system enhances the outcome by introducing the novel technique of CBIR system. Therefore, the significant contribution of the proposed system is to design a novel CBIR technique that uses cost-effective and yet computational efficient feature extraction techniques (using visual content descriptors) for better retrieval outcomes.

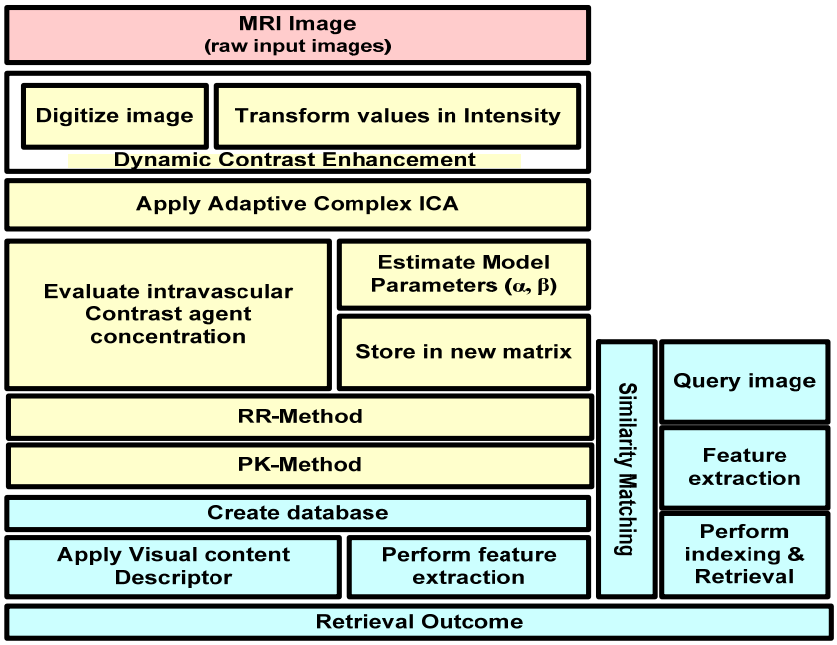


Figure 1: System Architecture

4. Implementation

The proposed system is implemented in 32 bit Windows operating system using Matlab as a programming tool. The system has got two modules i) diagnosis and ii) CBIR. MRI image is considered as input image which after subjected to propose architecture gives the output as retrieved image with prostate cancer detection. proposed model is classified into 3 sub-process viz. i) Dynamic Contrast Enhancement (DCE-MRI), ii) Adaptive Complex ICA (ACICA), and iii) Content based Image Retrieval (CBIR). The input MRI image is considered, which after performing digitization is converted to grayscale for easiness in computation. The grayscale image is then subjected to transformation towards enhancing its image intensity. After considering the enhanced image from sub-process, the process captures the real and imaginary part of the image component, which is then subjected to Gaussian distribution. The output of the process is then evaluated to estimate the model parameters, followed by probability density function (PDF) for the purpose of extracting non-linearity. Finally, the independent components are derived, which will be used by CBIR system in the latter part. It basically works in two stages. In the preliminary state, the outcome of the independent components and image information is considered as an input for creating the database. Applying visual content descriptor, the feature will be extracted. In the next phase, the query image is subjected to similar operation, where both the outcomes are subjected to similarity match. The matrix that computes similarity match finally performs indexing and retrieval of both the images from the database, finally yielding multiple sets of most match images as outcome of the system. Using adaptive complex ICA and CBIR system, thereby maintains better

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confirmation of the images relevant to specified clinical condition of prostate cancer.

The algorithm used in the design of the proposed system is as follows:

4.1. Algorithm for cancer detection using ACICA and CBIR

Input: MRI Image
Output: Retreived image with detection of prostate cancer
START
1. Take the input image
2. Convert to grayscale
3. Transform the intensity of an image
//Start ACICA Process
4. Apply Adaptive complex ICA
5. Evaluate intravascular curve
6. Apply Reference Region based method to correct intravascular curve
7. Apply Pharmacokinetic (PK)-modeling technique
8. Apply visual descriptors
9. Extract feature vectors
//Start CBIR Process
10. Create a database of feature vectors
11. Give query image
12. Perform Step 8 and 9
13. Perform similarity Match
14. Retrieve image
END
The prime purpose of the above discussed algorithm is to extract the intravascular contrast agent concentration (IVCA). The next algorithm uses a unique combination of 2 visual descriptions for the purpose of feature extraction viz. Color layout descriptor (CLD) and Edge Histogram Descriptor (EHD).

4.2. Algorithm for Feature Extraction

Input: Input image
Output: Extracted Features
START
1. Input image
//Implement CLD algorithm
2. Create one image to show the partitions
3. Show division on an image
4. Divide image in 8 x 8 blocks
5. Save block values in cell
6. Perform DCT on the block
7. Store the lowest frequency coefficient at respective place
8. Save the coefficients
9. Extract CLD
//Implement EHD algorithm
10. Vertical filter, horizontal filter
11. Divide image in 2x2 blocks
12. Initialize empty vector to store the histogram values
13. Multiply all filters with blocks
14. Find maximum value
15. If maximum value is more than threshold then it is a edge block
16. Increment respective value
17. Normalize the histogram
END

The prime purpose of the above discussed algorithm is to extract the feature vectors from database and query image. The CBIR part of the algorithm will tend to use the visual descriptors. Tentatively, the project will use Edge Histogram Descriptor and Color Layout Descriptor, which is basically a color and texture based general information descriptors. The visual descriptor will enable the extraction of the features effectively for various ranges of medical images and permits the effective retrieval of CBIR process that is faster and efficient compliant with time and space complexity. Hence, it is anticipated that the outcome of the CBIR system is highly efficient and cost effective in terms of prostate cancer detecti

5. Results

The results show that there is a high value in the region in the peripheral zone of the prostate that was hypo-intense in both apparent diffusion coefficient map and T2-weighted MRI. Moreover the results are compared with the parameters derived using a large artery and also corrected artery as the intravascular concentration curve. Clustering is a form of unsupervised classification that aims at grouping data points based on similarity. In this project we propose a new partitional clustering algorithm based on the notion of 'contribution of a data point'. We apply the algorithm to content-based image retrieval and compare its performance with that of the k-means clustering algorithm. Unlike the k-means algorithm, our algorithm optimizes on both intra-cluster and inter-cluster similarity measures. It has three passes and each pass has the same time complexity as iteration in the k-means algorithm.

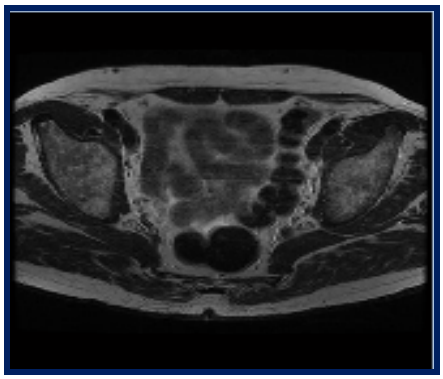


Figure 2: Input Image

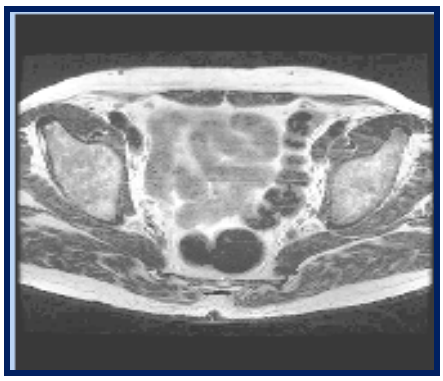


Figure 3: Dynamic Contrast Enhancement (DCE-MRI)

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The MRI-image of prostate cancer which is shown in Fig.2 is read as an input and it is subjected to perform DCE-MRI-in which the input MRI-image of prostate is first converted into grayscale, then it is subjected to transformation and then it renders the output as DCE-MRI which is show in Fig.3.

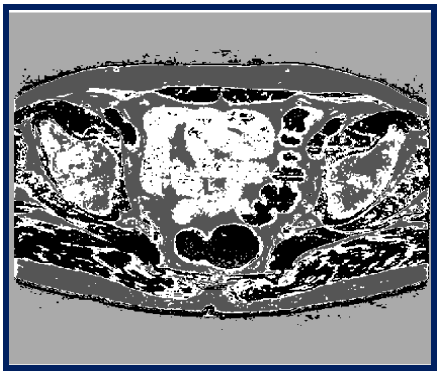


Figure 4: Agent Concentration by ACICA

After that Fig.3 is subjected to ACICA sub-process which is shown in Fig.4, so that it calculates the intravascular contrast agent (IVCA) concentration.



Figure 5: Reference Region

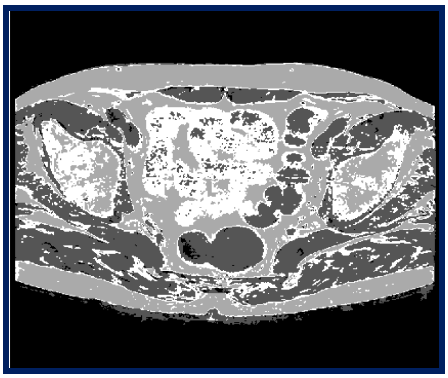


Figure 6: Agent Concentration by RR-Method

Then it is subjected to reference-region (RR) method which is shown in Fig.6, so that it corrects the concentration curve which is produced during the ACICA sub-process and the corresponding Histogram is generated as shown in Fig.7.

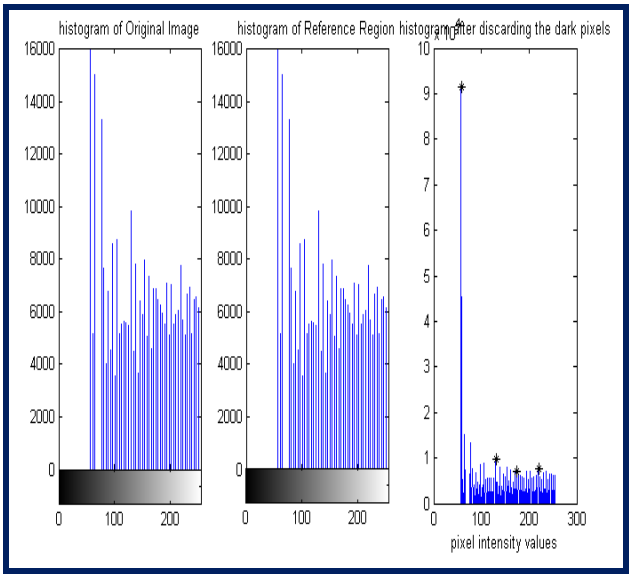


Figure 7: Histogram Analysis obtained after applying the RR-Method

The first and second histogram indicates the input MRI image and the reference region on which the RR-method is applied. Then, finally the third histogram is obtained after discarding the dark pixels.



Figure 8: Agent Concentration by PK-Modeling

After that Fig.6 is subjected to PK-Modeling which is shown in Fig.8, so that it reduce the false positives produced during the RR-method and the corresponding Histogram is generated as shown in Fig.9.

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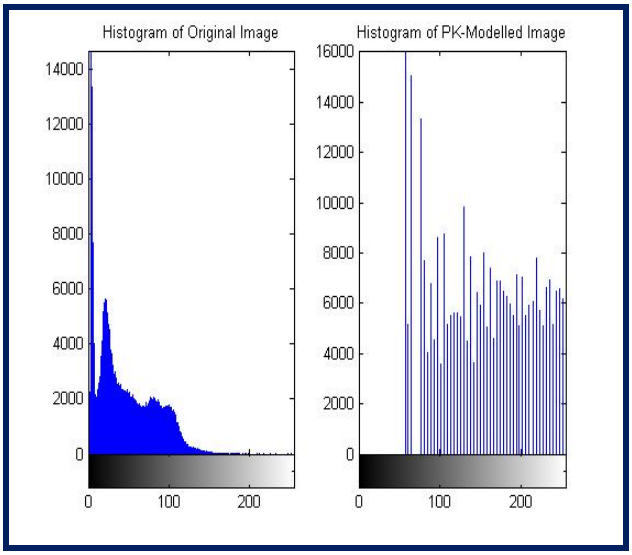


Figure 9: Histogram Analysis obtained after applying the PK-Modeling

Here, the first histogram indicates the input MRI image and the second histogram are obtained after applying PK-modeling.

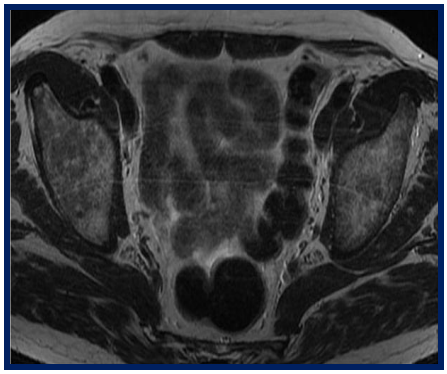


Figure 10: Suspected Region

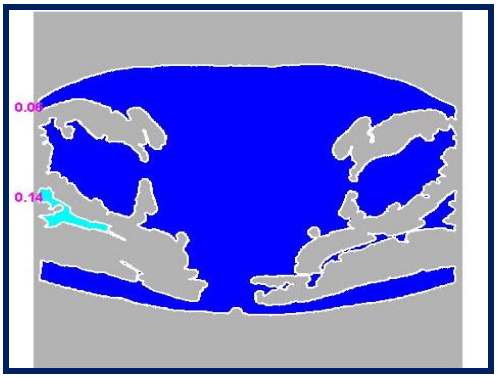


Figure 11: High contrast agent concentration region

Fig.10 shows the suspected region to be analyzed. Fig.11 shows the High agent concentration in the suspicious region. Here, the cyan color indicates the high contrast (0.14) and inturn it is indicated as suspicious region. The proposed system is based on the study performed by the author Hatef Mehrabian by the title "Using independent components analysis to calculate intravascular contrast agent concentration in prostate cancer [1]. However, the outcome, highlighted in our implementation is an enhanced version of the result obtained by [1]. It can be easily observed that agent concentration performed by adaptive independent component analysis, (ACICA), Pharmacokinetic Modeling (PK) and Reference Region (RR) method. Our enhanced result as shown in Fig.4, Fig.5, Fig.6, Fig.8, Fig.10 and Fig.11 are the enhanced version of their previous outcome of the existing system. The precision of the system is rendered more smartly by incorporating Content based Image Retrieval System (CBIR), where the retrieval of the similar images are done by extracting the features from the queried image from the visual descriptors. We chose to use color layout descriptor (CLD) and Edge Histogram Descriptor (EHD) for better precision of the outcome of the similar images in proposed CBIR system.

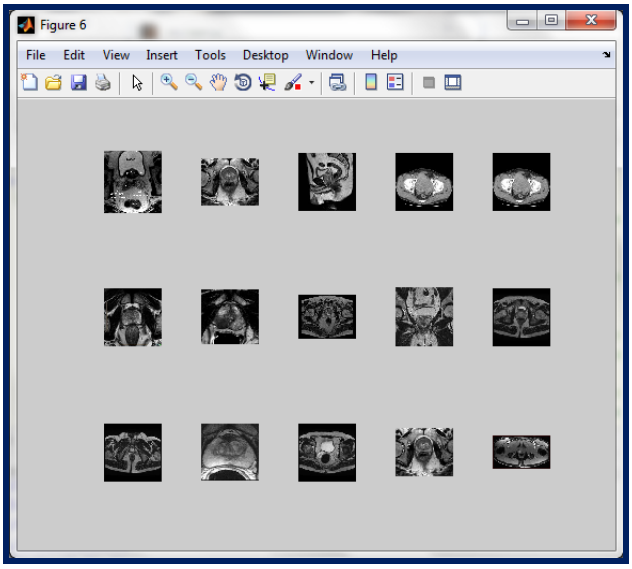


Figure 12: Outcome of Retrieved images

6. Conclusion

In this study a method is introduced to calculate the intravascular concentration in the prostate tissue using an adaptive complex independent components analysis (ACICA) method and to correct this curve for the early phases of the passage of the contrast agent through tumor vasculature. The results are applied to DCE-MR images of the prostate of a 70 year old prostate cancer patient and the calculated map is examined using tumor location defined by multi-parametric MRI.

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