Medical Image Retrieval Using Visual and Semantic Features

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***Abstract*— Medical images are being digitized and the medical databases are rapidly growing. These images are used in academics, diagnoses, and hospitals for planning treatment. Data mining techniques are applied to medical images, for a quick diagnosis. Thus, the technique of Content-based Medical Image Retrieval (CBMIR) emerges as the times require. For medical image retrieval, current CBMIR is not sufficient to capture the semantic content of an image and difficult to provide good results according to the predefined categories in the medical domain by using less medical knowledge. In this paper, the retrieval system is a combination of low-level image feature and high-level semantics and it includes three main parts: In the first part, the low-level fusion visual features are extracted based on intensity, texture, and their extended versions. Secondly, a set of disjoint semantic tokens with appearance in lung CT images is selected to define a vocabulary based on medical knowledge representation. Finally, a mapping is investigated to associate low-level visual image features with their high-level semantics. In this paper a mapping modelling of visual feature and knowledge representation is presented to approach for medical image retrieval. One important contribution of this paper is the use of physicians defined linguistic variables closely related to known pathologies. This framework could be the foundation of building a novel and flexible model for diagnostic medical image retrieval that uses physician-defined semantics.**

Keywords- Medical image retrieval; low-level features; knowledge representation; semantic Features.

I. INTRODUCTION

With the increasing influence of computer techniques on the medical industry, the production of digitized medical data is also increasing heavily. In recent years, rapid advances in software and hardware in the field of information technology along with a digital imaging revolution in the medical domain facilitate the generation and storage of large collections of images by hospitals and clinics. Though the size of the medical data repository is increasing heavily, it is not being utilized efficiently, apart from just being used once for the specific medical case diagnosis. In such cases, the time spent on the process of analyzing the data is also being utilized for that one case only. But, if the time and data were to be utilized in solving multiple medical cases then, the medical industry can benefit intensively from the medical experts' time in providing new and more effective ways of handling and inventing medical solutions for the future. This can be made possible by combining two most prominent fields in the field of computer science – *data mining techniques* and *image processing techniques.*

Medical imaging is the technique used to create images of the human body for medical procedures (i.e., to reveal, diagnose or examine disease) or for medical science. Medical imaging is often perceived to designate the set of techniques that noninvasively produce images of the internal aspect of the body. Due to increase in efficient medical imaging techniques, there is an incredible increase in the number of medical images. These images, if archived and maintained, would aid the medical industry (doctors and radiologists) in ensuring efficient diagnosis.

The core of the medical data are the digital images, obtained after processing the X-ray medical images; these should be processed in-order to improve their texture and quality using image processing techniques and the data mining techniques may be applied in-order to retrieve the relevant and significant data from the existing million of tons of medical data with the entire manual way to maintain the image data, which is inefficient in meeting the needs of searching with the huge medical image database and is affecting the function of the image used in the diagnoses adversely? Thus, the technique of Content-based Medical Image Retrieval (CBMIR) is considered to be an effect way to tackle the problem. In specialized fields, namely in the medical domain, absolute color or grey level features are often of very limited expressive power unless exact reference points exist as it is the case for computed tomography images [13]. In the medical image system, low-level visual features (e.g., color, texture, shape, edge, etc.) are generated in a vector form and stored to represent the query and target images in the database. Queries by image content require that, prior to storage, images are processed, and appropriate descriptions of their content are extracted and stored in the database [28]. When a user makes a query, medical image retrievals are performed based on computing similarity in the feature space and most similar to the query image are returned to the user based on similarity values computed.

A diagnosis by a specialist often requires a visit to a radiology department to obtain various images that highlight the suspected pathology. Despite the high resolution of the acquired images, image-based diagnosis often utilizes a considerable amount of qualitative measures. To improve the diagnosis and efficiency, the research in medical image analysis has focused on the computation of quantitative measures by automating some of the error-prone and time-consuming tasks, such as segmentation of a structure.

The Bag Of visual Words (BoW) model is commonly used in natural language processing and information retrieval for text documents [1]. In this model, a document is modeled as an instance of a multinomial word distribution and it is represented as a frequency of occurrence word histogram. The representation as a frequency vector of word occurrences does not take grammar rules or word order into account. It preserves key information about the content of the document. This representation can be used to compare documents, and to identify document topics. The BoW representation is successfully used in document classification, clustering, and retrieval tasks and is the cornerstone of all Internet search engines [1].

To represent an image using the BoW model, the image must be treated as a document. Unlike the text world, there is no natural concept for a word or a dictionary. Thus there is a need to find a way to break down the image into a list of visual elements (patches), and a way to differentiate the visual element space, since the number of possible visual elements in an image is very huge. In the visual BoW model, the image feature extraction step takes place in a procedure involving detection of points-of-interest, feature description, and codebook generation. The visual word Model can thus take the form of a histogram representation of the image, based on a collection of its local features. Each bin in the histogram is a codeword index out of a finite vocabulary of visual code words, generated in an unsupervised way from the data. Images are compared and classified based on this discrete and compact histogram representation.

In recent years, the Bow approach has successfully been applied to general scene and object recognition tasks [9] [11] [19]. Varma et al.[19], introduced the idea of using the joint distribution of intensity values over compact neighborhoods for the task of texture classification was introduced. In vector quantization of invariant local image, descriptors were used to form clusters, referred to as visual "words." They then searched for objects throughout a movie sequence by analogy to text retrieval. Natural scene categories were learned using visual words in [11]. Local words were either grayscale patches or scale-invariant feature transform (SIFT) descriptors [26], sampled on a grid, randomly, or at interest points. Then, they then learned a generative hierarchical model to describe the resulting visual word distribution. Spatial pyramids [34] were introduced as a technique of partitioning the image into increasingly fine sub regions, and computing histograms of local features within each sub region.

In this paper , Section II describes the existing systems for medical image retrieval, limitations of the existing system thus motivation and advantages of the proposed system. Section III presents the Architecture of the system and the methods followed to retrieve the result. Section IV depicts the module that is developed to retrieve the result. Section V illustrates the overall work done for implementation and Future work.

II.STATE OF THE ART

In picture archiving and communication system (PACS), image information is retrieved by using limited text keyword in special fields in the image header (e.g., patient identifier). Content-based image retrieval (CBIR) has received significant attention in the literature as a promising technique to facilitate improved image management in PACS system [13][16]. The Image Retrieval for Medical Applications (IRMA) project [16][38] aims to provide visually rich image management through CBIR techniques applied to medical images using intensity distribution and texture measures taken globally over the entire image. This approach permits queries on a heterogeneous image collection and helps in identifying images that are similar with respect to global features e.g., all chest x-rays in the AP (Anterior-Posterior) view. The IRMA system lacks the ability for finding particular pathology that may be localized in particular regions within the image. In contrast, the Spine Pathology and Image Retrieval System (SPIRS) [39][40][41] provides localized vertebral shape-based CBIR methods for pathologically sensitive retrieval of digitized spine x-rays and associated person metadata. Image Map [42] is so far, the only existing medical image retrieval that considers how to handle multiple organs of interest and it is based on spatial similarity. Consequently, a problem caused by user subjectivity is likely to occur, and therefore, the retrieved image will represent an unexpected organ. ASSERT [43] (Automatic Search and Selection Engine with Retrieval Tools) is a content–based retrieval system focusing on the analysis of textures in high resolution Computed Tomography (CT) scan of the lung. In WebMIRS [44] system, the user manipulates GUI tools to create a query such as, "Search for all records for people over the age of 65 who reported chronic back pain. Return the age, race, sex and age at pain onset for these people." In response, the system return values for these four fields of all matching records along with a display of the associated x-ray images. So there is a need of absolute error free, efficient and automatic CBMIR system which can really helpful in medical stream.

Medical images are being digitized and the medical databases are rapidly growing. These images are used in academics, diagnoses, and hospitals for planning treatment. The existing CBMIR [3] systems are capable of retrieving medical images. They take input as an image and produce results that match the low level features of the image. Visual

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features such as color, shape and texture are implemented for retrieval of images in CBMIR [3].

Limitations / Disadvantages of the existing System

- The current CBMIR is not sufficient to capture the semantic content of an image [9] because CBMIR is a technique for retrieving image on the basis of automatically derived features such as color, texture and shape to index images with minimal human intervention.
- Therefore it is difficult to provide good results according to the predefined categories in the medical domain for less using the medical knowledge.

- Accordingly, in this paper, a mapping model of visual feature and knowledge representation is proposed.

- The proposed approach is described in the following section which takes the advantage of semantic feature retrieval along with the visual features of the medical images.

III. PROPOSED SYSTEM

A. System Overview

In this paper, we propose to use medical concepts based on medical knowledge to represent lung CT image. It allows our system to work at a higher semantic level and to standardize the semantic index of medical data, facilitating the communication between visual and textual indexing and Retrieval. Here, a concise presentation of the main theme of this paper is given.

As depicted in Fig. 1, the main components in Essence are: 1) *Semantic domain*; 2) *Images space*; 3) *Feature extraction algorithms*; 4) *Feature domain*; 5) *Query system*;. Knowledge components are represented in rectangles, and knowledge-driven actions, such as search and discovery, are represented in oval shapes.

The *Semantic domain* is organized as a local-as-view data integration subsystem [35]. This system let users build, refine, and further decompose their semantics independently, with minimum effort. The *Semantic domain* represents the expert's knowledge in an XML format. Using a similar format, the framework represents the knowledge of a specific case, a medical image, in *Feature domain.*

Each element in the *Feature domain* is a signature of a medical image in the *Image space*. The signature is computed by executing the *Feature extraction algorithms.*

The *Query system* searches the knowledge base, selects relevant images, and translates the result into a human-readable format. It provides two mechanisms to access the knowledge: 1) query by semantics and 2) mapping low level features with semantic terms.

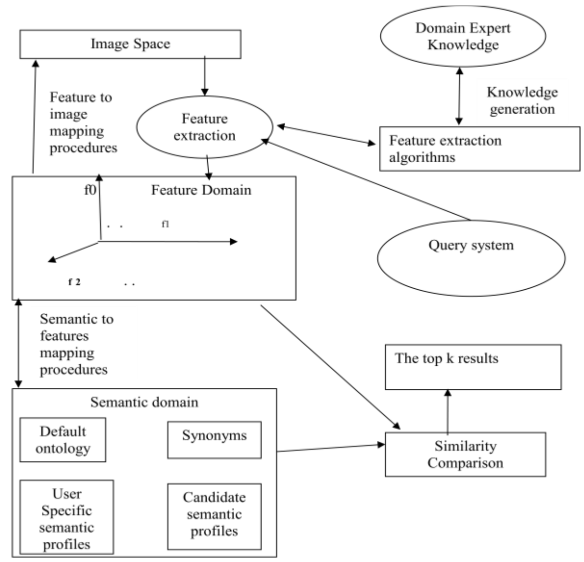

Figure 1. Proposed System Architecture

In the first part, the low-level fusion visual features are extracted based on intensity, texture, and their extended versions. Secondly, a set of disjoint semantic tokens with appearance in lung CT images is selected to define a vocabulary based on medical knowledge representation. Finally, a mapping is investigated to associate low-level visual image features with their high-level semantics.

IV. IMPLEMENTATION

This section describes about the implementation of each module like Pre-Processing, Feature Extraction, mapping algorithm, in which detailed description of each module is give below.

A. Pre-Processing

Pre-processing includes the process of removing the unwanted data from the image and improves the quality of the images. This process of removing unwanted data (like stop-words in the data mining process) can be achieved by the techniques such as *cropping, image enhancement, etc.* In this section, a series of effective pre-processing methods [31] are adopted to extract the pulmonary parenchyma which will improve the quality of feature extraction and then increase the retrieval performance in accuracy and speed. The process of extraction of pulmonary parenchyma is as follow.

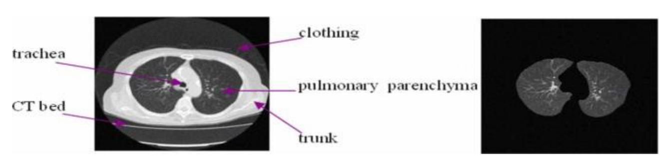

Figure 2. Pre-processing Result

Step 1: Cutting out the background region

- First, pre-processing is applied to the original CT scan image. Both lungs and their nearby portions are areas of interest and pixel values external to this area being insignificant are removed.

Step 2: Segmentation with optimal threshold and noise Cancellation

- The next step is applying threshold to the image to achieve two categories of pixels in the image or a binary image. Then tested for separation of left and right lungs if no threshold value is adjusted.

Step 3: Elimination of trachea and main bronchus.

- During acquisition or digitization process of CT scan images a noise could be introduced that needs to be reduced. An appropriate filter need to be chosen which can enhance the image quality even for non uniform noise, like salt and pepper noise, and also preserve the important edges.
- There may be the presence of noise and other components, i.e., airways and bronchi in the image. These components are to be eradicated.
- It is evident that two major objects in the threshold image are both lungs. Connected component analysis is applied here.
- The connected component labelling algorithm assigns distinct labels to all the regions in the image so as to manipulate the regions fulfilling the specific criteria set for regions. Keeping this in view, extract the two largest components.

Step 4: Adaptive segmentation of left and right lung

- A fully automatic method based on adaptive thresholding for segmenting the lungs in three-dimensional (3-D) pulmonary X ray CT images consists of eight steps.
- In the first step, a threshold is selected to convert a CT image into a binary image.
- In the second step, the lung objects are removed from the ribcage to obtain the external mask.
- In the third step, the right and left lung area is extracted by applying the external mask.
- In the fourth step, the large airways are removed utilizing the mean and the deviation of pixel intensities.
- In the fifth step, a test is made to see if the selected threshold is good. If the selected threshold is not good, the
- Threshold will be adjusted and the algorithm goes back to step 1.
- In the sixth step, a morphology operation is applied to smooth the mediastinum.
- In the seventh step, a split curve is derived from the gap of the separated left and right lungs.
- In the last step, the left and right lungs are segmented.

Step 5: Refinement processing and mask generation

- The external mask is adopted to eliminate unwanted objects surrounding the lungs, so the whole lung region can be extracted precisely.
- To obtain the external mask, remove the two lungs to form the non-lung mask. And then the non-lung mask will be inverted to build the external mask.

Thus, pulmonary parenchyma is useful for the extraction of image feature. One of segmentation result is shown in Fig .2, various features such as trachea, CTbed will be extracted.

B. Low-Level Feature Extraction

Low-level image feature extraction is the basis of CBIR systems. To performance CBIR, image features can be extracted from the entire image.

- *Gray Level Co-Occurrence Matrix (GLCM) Statistical Feature Vector:*

  With the created GLCM [36], various features can be computed out. Fourteen parameters were summarized before, but with the special characteristics of lung CT image, four parameters are chosen to descript the texture. These feature description groups along with the images are in a database for the retrieval purpose.

  • Energy

  Measure the number of repeated pairs. The energy is expected to be high if the occurrence of repeated pixel pairs is high.

$$F_{ENE} = \sum_{j=0}^{N-1}.\sum_{j=0}^{N-1}[p(i.j)|d,\theta)]^2|(\mathrm{d},\theta)]^2 \quad (1)$$

  • Entropy

  Measure the randomness of a gray-level distribution. The entropy is expected to be high if the gray-levels are distributed randomly throughout the image.

$$F_{ENT} = \sum_{i=0}^{N-1}.\sum_{j=0}^{N-1}[p(i.j)|d,\theta)]\log[p(i,j|d,\ \theta)] \quad (2)$$

  • Contrast

  Measure the local contrast of an image. The contrast is expected to be low if the gray levels of each pixel pair are similar.

$$F_{CON} = \sum_{i=0}^{N-1}.\sum_{j=0}^{N-1}(i-j)^2\, p(i,j|d,\theta)|\mathrm{d},\theta) \quad (3)$$

  • Correlation

Provide a correlation between the two pixels in the pixel pair. The correlation is expected to be high if the gray levels of the pixel pairs

are highly correlated.

$$F_{COR} = \frac{\sum_{i=0}^{N-1} \cdot \sum_{j=0}^{N-1} ijp(i,j|d,\theta) - \mu_x \mu_y}{\sigma_x \sigma_y} \qquad (4)$$

Where μ_x, μ_y, σ_x, σ_y are mean value and standard variance of

$$p_x, p_y, p_x = \sum_{j=0}^{N-1} p(i,j \mid d,\theta), \; p_y = \sum_{i=0}^{N-1} p(i,j \mid d,\theta).$$

So, the above GLCM parameters are used as retrieval feature vector: $F_{GLCM} = \{F_{ENG}, F_{ENT}, F_{COR}, F_{LOC}\}$.And d= 1, $\theta = 0°, 45°, 90°, 135°$.

- *Wavelet Statistical Feature Vector:*

Wavelet transform [37] has been successfully used in image compression, enhancement, analysis, and classification. An image is a 2-D signal, so the 2-D discrete wavelet transform (DWT) can be implemented to approach to texture analysis.

In this paper, a multi-resolution representation is gotten by using 2-D wavelet transform with three-level decomposition. The statistical information, which is from the texture feature with different multi-resolution, will constitute the retrieval feature vector. When the distinct texture characteristics appear in certain frequency and direction the output of wavelet channel has more energy. So the mean and variance of energy distribution in every decomposition level can represent the texture feature. And we use the mean and variance of this energy as the retrieval feature vector F_{WAVL}. .

$$F_{WAVL} = \{E_{10}, E_{11}, E_{12}, E_{20}, E_{21}, E_{22}, E_{30}, E_{31}, E_{32}\} \qquad (5)$$

C. Knowledge Representation and Semantic Features Identification Phase

Most of the decisions in the medical domain are made by comparing the data in hand against existing domain knowledge. During the decision-making process, physicians base their diagnoses on a set of heuristics developed from different areas as a "multi-dimensional intuition" in which tacit knowledge plays a very important role. Several perceptual categories are usually used for recognizing pathologies in lung CT images by physicians.

In this phase, a set of disjoint semantic tokens with appearance in medical images is selected to define a vocabulary based on medical knowledge representation. Here we use the keywords of diagnosis report from the doctor to represent each token in the medical domain.

Semantic vocabulary used

1. Reticular Opacities
2. Nodular Opacities
3. High Density Areas
4. Low Density Areas
5. Cavitary
6. Cystic structure
7. Emphysema
8. Calcification
9. Honeycombing
10. hydrothorax

- *Mapping Algorithm*

The main difficulty in image retrieval based on semantics is to use image's low-level features to replace "word" (semantic) in the text retrieval.

1. A set of disjoint semantic concepts with visual appearance in medical images is first selected to define a vocabulary based on medical knowledge representation.
2. Low-level features are extracted from medical image *z* to represent each vocabulary term.
3. These low-level features are used as training examples to build hierarchical semantic classifiers according to the semantic vocabulary. The classifier for the medical semantic vocabulary is designed using a hierarchical classification scheme based on Support Vector Machine (SVM) classifiers.
4. Hierarchical classification scheme is based on Support Vector Machine (SVM) classifiers. A tree, whose leaves are the medical semantic vocabulary terms is designed and constructed in a top-down manner, guided by the possible hierarchy of the associated terms in semantic vocabulary. Fig. 3 depicts the tree. The upper levels of the tree consist of auxiliary classes that group similar terms with respect to their visual appearances.

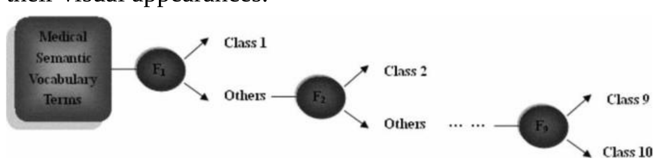

Figure 3. Tree Structure for Medical Semantic Vocabulary Classifier

D. Retrieval Phase

For training of SVM, 100 images with physicians labelling are selected as training set and rest of the images are utilized to test the retrieval approaches. For SVM based image classification, recent work shows that the Radial Basis kernel Function (RBF) works well when the relation between class labels and attributes is nonlinear [33].

Therefore, we use RBF kernel as a reasonable first choice. The RBF kernel function is

$$K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2), \gamma > 0 \qquad (6)$$

There are two tuneable parameters, while using RBF kernels: c and *r*. We define C =200 and *r* =0.0002 for example.

In this phase, the low level features are used as training examples to build a semantic classifier according to the above vocabulary. The visual feature and semantic feature are mixed as Indexing.

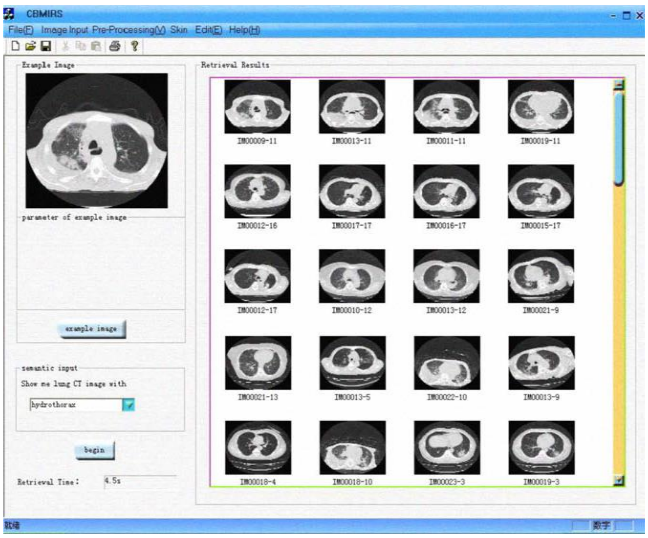

Figure 4. A Retrieval Result

In the experiments, every image from the test DB is served as a query image. We design two types of experiments to evaluate the retrieval system.

I) Retrieval based on low level features only. For every medical semantic category, we chose relevant image as example to conduct the retrieval.

2) Retrieval based on semantic description. For every medical semantic category 10 tests are conducted and 100 tests are conducted totally. One of semantic concept with hydrothorax retrieval results is shown in Fig. 4. Based on the input image as shown in the left top corner in Fig. 4, all the similar images from the database are retrieved.

Our system has a small knowledge base, which can be further enhanced. Ensemble classifiers can be used in the future work. Sophisticated knowledge representation algorithms may be considered.

E. *Evaluation of the Results*

Retrieval precision and ranking measures *(Average-r)* are used as parameters in system evaluation.

(I) The retrieval precision is defined as follows :

Precision = a / a+b (7)

Where *a* is the number of similar images and *b* is the number of dissimilar images in the results .

(2) Suppose the query is *q* , $r_1, r_2, \ldots r_m$ are the correct results retrieved by the system, *rank(r_j)* is the No. *j* correct result's ranking position, so the average ranking value is calculated as follows:

$$\text{Average-r} = 1/m \sum_{j=1}^{m} \text{rank}(r_j) \qquad (8)$$

This value reflects the average ranking of query in the retrieval results. So, the smaller it is, the better. In the experiment, we set m=10. The statistic results are shown in Table 1.

TABLE 1. The Experiment Static Result

	Low-level feature retrieval (%)		Semantic Vocabulary retrieval (%)	
semantic terms	*Precision*	*Average – r*	*Precision*	*Average – r*
Reticular Opacities	55.20	7.55	71.25	5.90
Nodular Opacities	66.50	6.80	66.35	6.55
High Density Areas	52.80	7.85	51.26	8.00
Low Density Areas	46.90	8.40	52.18	7.98
Cavitary	45.36	8.55	40.75	8.45
Cystic structure	49.58	7.95	40.65	8.64
Emphysema	40.20	8.75	45.78	8.30
Calcification	50.13	7.90	60.64	7.04
Honeycombing	60.15	7.00	70.56	6.00
hydrothorax	47.25	8.20	62.12	6.95

From the above statistic results , we can see that the image with outstanding texture information always get better precision and smaller average ranking value. For example the images which possess the pathological characteristics of nodular opacities and honeycombing get the best precision. This is Because the low-level feature extraction procedure is mainly used of texture analysis algorithm.

In addition, when the visual features are difficult to present the method use semantic correlation can put up a satisfied result. For above ten kinds of queries, the semantic correlation gets an average precision. So we can see the method we proposed has a good robustness.

V CONCLUSION AND FUTURE WORK

In this paper, visual, semantic features and knowledge representation are used for medical image retrieval. This framework could be the foundation for building flexible model for diagnosis of medical images. This framework can use physician-needed semantics. The expressions of diseases in medical image are complex and various. From the statistical results, the image with outstanding texture information always gets better precision and smaller average ranking value. The images which possess the pathological characteristics of nodular opacities and honeycombing get the best precision. In addition, when the visual features are difficult to present the method uses semantic correlation, which can put up a satisfied result .Our results prove that our proposed system has good robustness.

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