An Improved Naive Bayes Classification to Enhance Image Registration

Mohammed Imran[1], M. Babu Rao[2] , Ch. Kavitha[3]

[1](*M Tech, GEC, Gudlavalleru,)*
[2]*(Professor of CSE, GEC, Gudlavalleru).*
[3]*(Professor of IT, GEC, Gudlavalleru.)*

Abstract – Image registration based classification is among the important image processing procedures in medical imaging and remote sensing, it has been developed and studied for a long time. Complex image registration issue arising as the dependencies between intensities of images to remain registered are not spatially homogeneous. However, as yet, it is still rare to locate a reliable, robust, and automatic image registration method, and most existing image registration methods are intended for particular application. At present, high resolution remote sensing or medical images have used it more convenient for people to study, however, in addition they bring some challenges regarding the traditional research methods. In terms of image register, there are some problems with using existing image registration techniques for high quality images, namely: (a) precisely locating control points isn't as simple as with moderate resolution images; (b) manually picking the large number of control points necessary for precise registration is tedious and time consuming; (c) high data volume will adversely influence the processing speed within the image registration; and (d) local geometric distortion can not be removed thoroughly using traditional image registration methods even with enough control points. In accordance to these reasons, the demand for an image registration approach that could resolve those issues is need to improve. We present Local Naive Bayes Nearest Neighbor, an improvement onto the NB image classification algorithm that increases classification accuracy and improves its ability to scale to high object classes. The important observation may be that only the classes represented in the local neighborhood regarding a descriptor contribute significantly and reliably on their posterior probability estimates. Alternatively to maintaining a separate search structure for each individual class, we merge all the reference data together into one search structure, providing fast recognition of a descriptor's local neighborhood. This proposed approach improves classification accuracy when we ignore adjustments to the more distant classes and shows that the run time grows with the log of the number of classes instead of linearly in the number of classes as did the original. In association with classification technique a log polar registration module is introduced to improve arbitrary rotation angles and a wide range of scale changes. This serves to furnish a good early estimation for the optimization-based affine registration stage. This proposed work will overcome the existing deficiencies in terms of accuracy and experimental results.

Keywords *– Classification, Image Registration, Naïve Bayes, Image classification.*

I. INTRODUCTION

Image classification attempts to provide useful suggestions for some applications that range from automatic diagnosisin medical systems to aim at recognition in remote sensing images. Important visual properties for instance shape, texture, and color are often made use to describe images in recognition applications. The term digital image refers to processing belonging to two dimensional picture using a digital computer. Within a broader context, it implies digital processing of almost any two dimensional data. A digital image can be considered an array of real or complex numbers represented by a finite number of bits. An image given in the sort of a transparency, slide, photograph or perhaps an X-ray is first digitized and stored as a matrix of binary digits in computer memory. This digitized image can then be processed and/or exhibit a high-resolution television monitor. For display, the reputation is kept in a rapid-access buffer memory, which refreshes the monitor on a rate of 25 frames per second to produce a visually continuous display. An image processor does the functions of image acquisition, storage, preprocessing, segmentation, representation, recognition and interpretation and ultimately displays or records the finished result is a image. The following block diagram gives the fundamental sequence involved with an image processing system. As detailed within the diagram, step one in the process is image acquisition by an imaging sensor along with a digitizer to digitize the image. The next thing is the preprocessing step where the image is enhanced being fed as an input into the other processes.

In order to best represent images, one common strategy consists in identifying possibly the most accurate feature vector (description).However, in many instances there are plenty of features you can find possessing reasonable performance. By means of these situations, one may employ feature combination approaches in order to strengthen their individual recognition rates, since different features may provide different, but complementary details about images. Several works cope with the issue by getting to know the most reliable features and weighting them as per some "reliability"-based measure [1]. Other works address this difficulty through the use of Linear Discriminant Analysis [4] and Principal Component Analysis in the following figure [1].

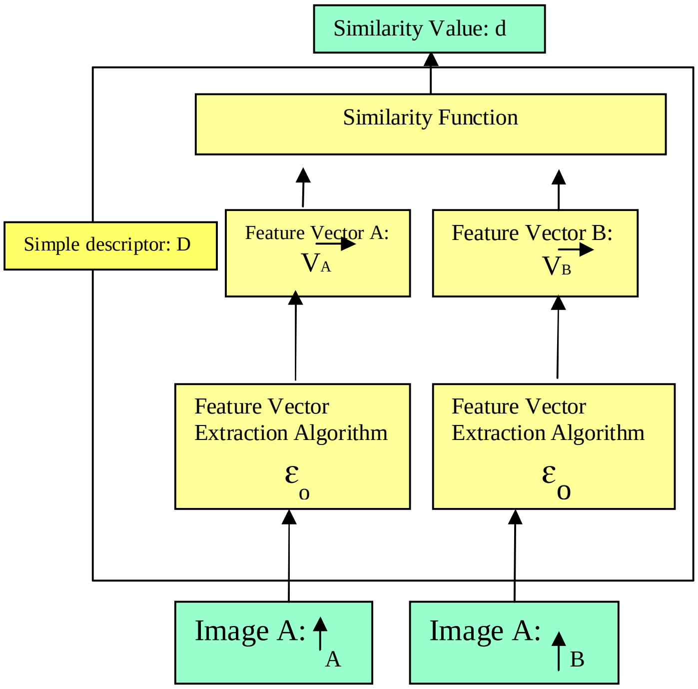


Figure 1: Linear Discriminant Analysis

Preprocessing typically relates to enhancing, removing noise, isolating regions, etc. Segmentation partitions an image into its constituent parts or objects. The output of segmentation is often raw pixel data, which consists of either the boundary of one's region or even the pixels inside the region themselves. Representation will be the strategy of transforming the raw pixel data into a form used by subsequent processing through computer. Description relates to extracting features that are basic in differentiating one division of objects from another. Recognition assigns a label to an object according to the information from the descriptors. Interpretation involves assigning importance an ensemble of recognized objects. Information about a problem domain is incorporated into information base. The knowledge base guides the operation of each processing module in addition to controls the interaction amongst the modules. Not all the modules necessarily present to produce a specific function. The composition of one's of a given image processing system depends upon its application. The frame rate of a given image processor is commonly around 25 frames per second[6-8].

II. LITERATURE SURVEY

Existing Nearest neighbor search is one of the most popular learning and classification techniques introduced by Fix and Hodges[1], which has been proved to be a simple and powerful recognition algorithm. Cover and Hart [2] showed that the decision rule performs well considering that no explicit knowledge of the data is available. A simple generalization of this method is called K-NN rule, in which a new pattern is classified into the class with the most members present among the K nearest neighbors, can be used to obtain good estimates of the Bayes error and its probability of error asymptotically approaches the Bayes error [3].

The Fourier-Mellon transform has been introduced to register images that are misaligned due to translation, rotation, and scale [4, 5, 6, 7]. This method applies a Fourier transform to images to recover translation. Then a log-polar transformation is applied to the magnitude spectrum and the rotation and scale is recovered by using phase correlation in the log-polar space. Furthermore, the log-polar transformation causes rotation and scale to be manifest as translation, whereby phase correlation can be applied to recover the rotation angle and scale factor between the pair of input images. The problem here, though, is that limited scale factors can be determined because large scale factors would alter the frequency content beyond recognition. It should be noted that the maximum scale factor recovered in [6] and [7] is 2.0 and 1.8, respectively. The primary drawback of the optimization-based approaches that it may fail unless the two images are misaligned by a moderate difference in scale, rotation, and translation.

Behmo et al. corrects NBNN for the case of unbalanced training sets. Behmo et al. implemented and compared a variant of NBNN that used n 1-vs-all binary classifiers, highlighting the effect of unbalanced training data. The method we will introduce is a local nearest neighbor modification to the original NBNN. Other methods taking advantage of local coding include locality constrained linear coding and early cut-off soft assignment by [5].Both limit themselves to using only the local neighborhood of a descriptor during the coding step. By restricting the coding to use only the local dictionary elements, these methods achieve improvements over their non-local equivalents. The authors hypothesize this is due to the manifold structure of descriptor space, which causes Euclidean distances to give poor estimates of membership in codewords far from descriptor being coded [5].

The traditional KNN text classification has three limitations [4]. High calculation complexity: To find out the k nearest neighbor samples, all the similarities between the training samples must be calculated. When the number of training samples is less, the KNN classifier is no longer optimal, but if the training set contains a huge number of samples, the KNN classifier needs more time to calculate the similarities. This problem can be solved in 3 ways: reducing the dimensions of the feature space; using smaller data sets; using improved algorithm which can accelerate to [5]. Dependency on the training set: The classifier is generated only with the training samples and it does not use any additional data. This makes the algorithm to depend on the training set excessively; it needs recalculation even if there is a small change on training set. No weight difference between samples: All the training samples are treated equally; there is no difference between the samples with small number of data and huge number of data. So it doesn't match the actual phenomenon where the samples have uneven distribution commonly.

A. Bayesian Framework

Prior distribution is used as a regularity term to enforce:

- the smoothness of the deformations φ main feature is the introduction and the estimation of a pixel classification to take into account the spatial variations of the statistical
- Relationships between the intensities.
- Numerical resolution of the combined registration and classification problem using the gradient descent algorithm.

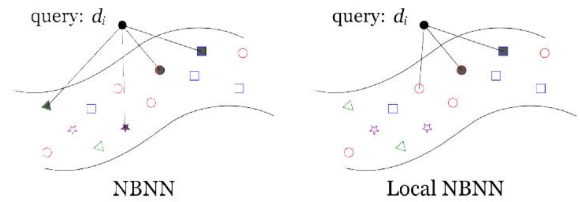
B. PROBLEMS IN EXISTING WORK:

- Existing Bayesian framework depends on local intensities values for image classification.
- Problem in image deformation using target image.
- Lack of image enhancing approach while applying the image deformation or image registration approaches.
- Existing Naïve bayes estimation are based on mixture models and characterize outliers by some specific probability distributions.

III. PROPOSED SYSTEM

A. Local Naive Bayes nearest Neighbor for Image Classification.

The selectivity introduced in the previous section shows that we do not need to update each class's posterior for each descriptor. This section shows that by focusing on a much smaller, local neighborhood (rather than on a particular log odds threshold), we can use an alternate search strategy to speed up the algorithm, and also achieve better classification performance by ignoring the distances to classes far from the query descriptor. Instead of performing a search for a query descriptor's nearest neighbor in each of the classes' reference sets, we search for only the nearest few neighbors in a single, merged dataset comprising all the features from all Labelle training data from all classes. Doing one approximate k-nearest-neighbor search in this large index is much faster than querying each of the classes' approximate-nearest-neighbor search structures [8].



NBNN finds the nearest neighbor from each of the classes (the shapes, in this figure). Local NBNN retrieves only the local neighborhood, finding nearest neighbors from only some of the classes. The shaded descriptors are those that would be used for updating the distance totals. We only use the closest member from any class, and don't find an example from each class.

Algorithm:

Require: A nearest neighbor index comprising all descriptors, queried using NN(descriptor;#neighbors).
Require: A class lookup, Class(descriptor) that returns the class of a descriptor.
for all descriptors di belongs Q do
{p1; p2; : : : ; pk+1} NN(di; k + 1)
distB ←||di- pk+1||^2
for all categories C found in the k nearest neighbors do
distC = min{pj |Class(pj)=C} ||di – pj||^2
totals[C] ←totals[C] + distC - distB
end for
end for
return argminC totals[C]

B. IMAGE REGISTRATION USING LOG-POLAR TRANSFORM

Log-polar registration module that serves as a preprocess to the parameter estimation module. Although the parameter estimation method features sub-pixel accuracy, the two images to be register. Must first be fairly close in scale (within a factor of two), rotation (within 450), and translation. The purpose of the newly added module is to account for large geometric transformations, bringing images into close alignment even in the presence of large (ten-fold) scale changes, as well as arbitrary rotations and translations.

$$r = \sqrt{(x-x_c)^2+(y-y_c)^2}$$
$$a = tan^{-1}\left(\frac{y-y_c}{x-x_c}\right)$$

Applying a polar coordinate transformation to an image maps.

1. Crop central region I_1' from I_1
2. Compute I_{1p}', the log-polar transformation of I_1'
3. For all positions (x, y) in I_2:

   Crop region I_2'

   Compute I_{2p}'

   Cross-correlate I_{1p}' and $I_{2p}' \rightarrow (dx, dy)$

   If maximum correlation, save (x, y) and (dx, dy)
4. Scale $\leftarrow dx$
5. Rotation $\leftarrow dy$
6. Translation $\leftarrow (x, y)$

Applying a polar coordinate transformation to an image maps radial lines in Cartesian space to horizontal lines in the polar coordinate space [5]. We shall denote the transformed image . If we assume that and lie along the horizontal and vertical axes, respectively, after a polar coordinate transformation. Note that the origin in both coordinate systems is taken to be in the upper left corner. The benefit of this new coordinate space is that simple scale and rotation changes may be induced by modifying the data. For instance, a circular shift along the axis in induces a rotation of . Recall, after all, that the data stored along the rows in -space represent radial data in . By moving the rows up or down, that radial data will map to a new (rotated) set of radial lines.

IV. RESULTS

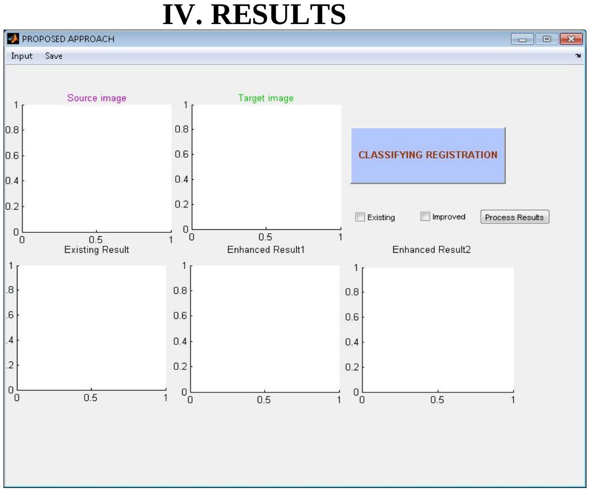


Figure 2: Front End view of the Proposed Approach

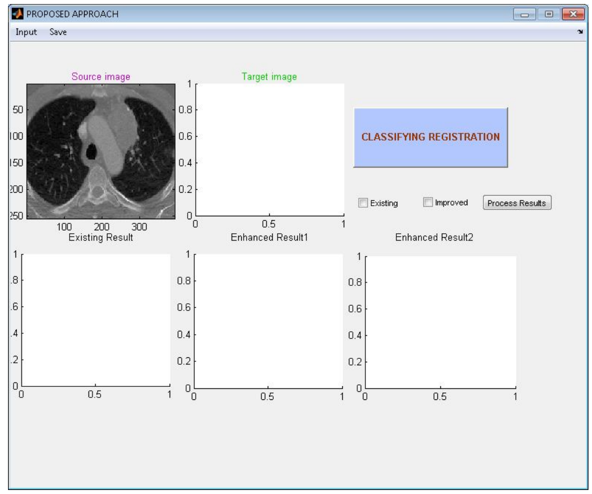


Figure3: Loading source image

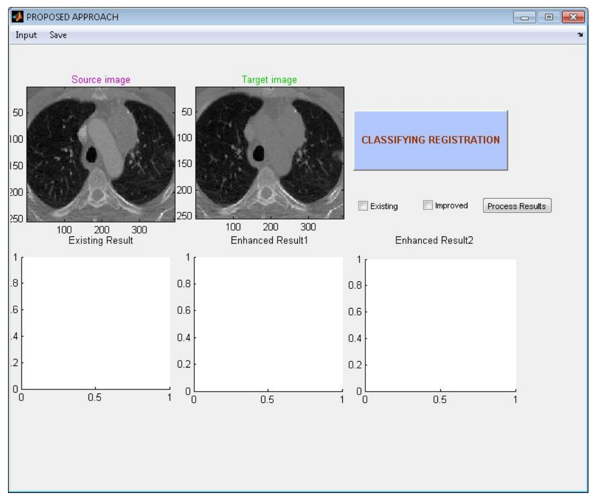


Figure 4: Loading Target Image

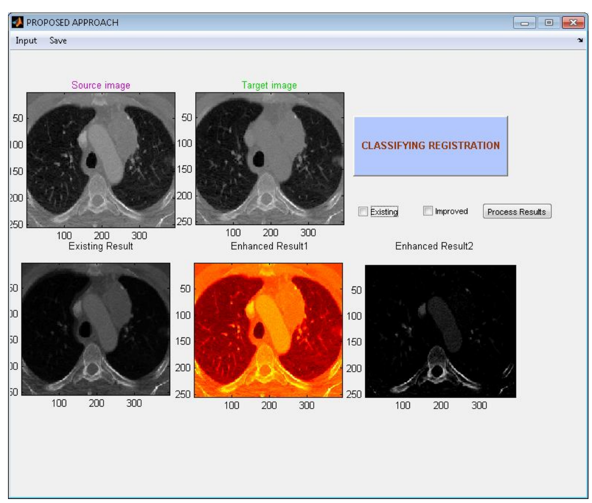


Figure 5: Applying classification based registration process

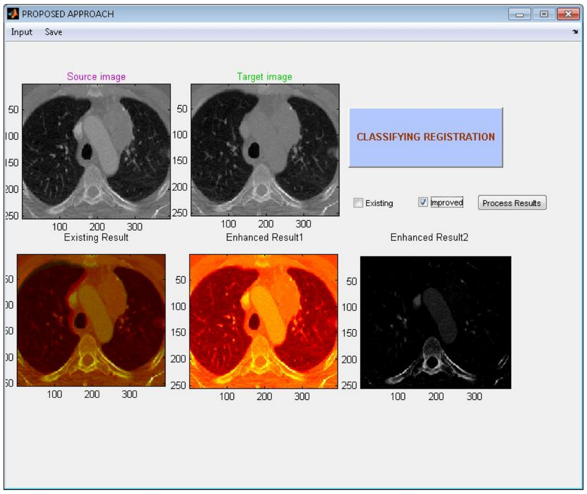


Figure 6: Results of Improved Approach

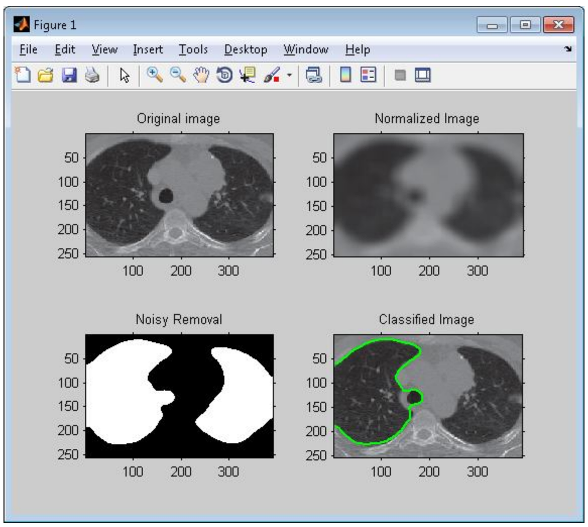
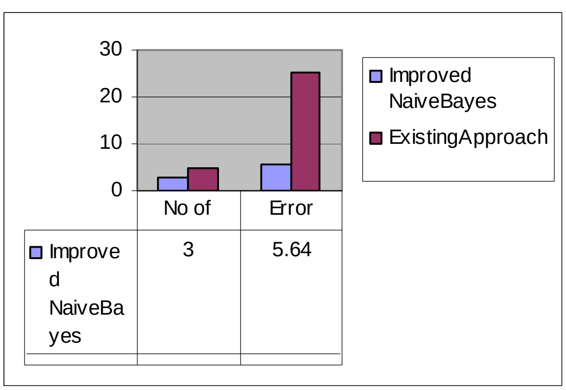
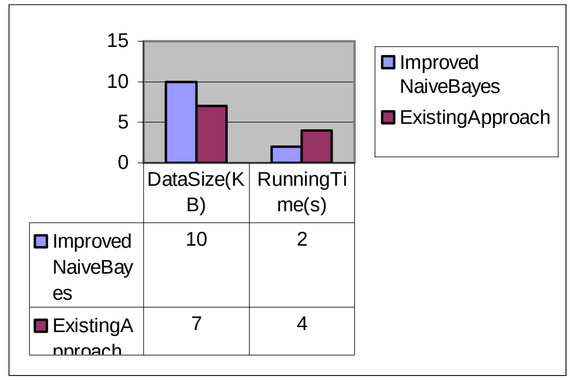


Figure7: Features extracted in proposed approach



Comparative graph between Number of features extracted vs Error rate in existing and proposed work



Comparative graph between Image data size vs. Running Time in existing and proposed work

V. CONCLUSION AND FUTURE SCOPE

The integrated novel classification algorithms for image classification are tested with medical images. We found that the proposed approach is performing well compared to the earlier. These algorithms are robust and very effective in producing. Desired classifications especially in the field of pattern recognition as per the region of interest as demonstrated by the experimental results. In future different neural network algorithms can be used to classify the medical to improve the better classification of multiple image registration results of those will be compared with the proposed algorithms.

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