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AN IMPROVED PSO BASED COEFFICIENT SELECTION FOR MEDICAL IMAGE FUSION

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Abstract: **-Medical imaging has become a vital component in routine clinical applications such as diagnosis and treatment planning. Therefore, image fusion techniques, which provide an efficient way of combining and enhancing information, have drawn increasing attention from the medical community. In this project, we propose PSO algorithm to select the coefficient efficiently.The algorithm is applied to coefficients extracted by two feature extraction techniques: the discrete cosine transforms (DCT) and the discrete wavelet transform (DWT). The proposed PSO-based feature selection algorithm is utilized to search the feature space for the optimal feature subset where features are carefully selected according to a well-defined discrimination criterion. Experiments demonstrate that our proposed algorithm generates better results than existing ones.**

Indexterms**—fusion rule, medical image fusion, multi scale analysis, PSO Algorithm.**

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I. INTRODUCTION:

Imaging Fusion techniques is used for medical imaging applications, such as diagnosis and treatment planning. Each and every imaging have certain modality, it provides information in a limited , joint analysis of medical imaging data collected from the patient using different modalities. The goal of image fusion is to provide a single fused image, such an enhanced image facilities visual perception (e.g.by a radiologist) or further image processing (e.g. by a computer-aided detection/diagnosis system ,i.e., a CAD system) Mostly the medical images are taken from MRI (Magnetic Resonance Imaging) scans and CT (Computed Tomography).For instance, T1-Weighted (T1W) and T2- Weighted (T2W) MRI scans were fused to segment while matterlesions or cerebral iron deposits and to guide neurosurgical resection of epileptogenic lesions. CT and MRI images are fused for neuronnavigation in skull base tumor surgery. PET (Positron Emission Tomography) and MRI images are combined and, it has proven useful for hepatic metastasis detection and intracranial tumor diagnosis

Fusion of SPECT (Single-photon emission computed tomography) and MRI images, for abnormality localization in patients with tinnitus. Individual Fetal cardiac ultrasound scans werefused to reduce imaging artifacts. Another one advantages of image fusion over side-by-side analysis of non-fused images have been demonstrated in lesion detection and localization in patients with neuroendocrine tumor and in patients with pretreated brain tumor also.A horizontal level individual model image fusion method is to overlay the source image by manipulating their transparency attributes and also assigning them to different color channels. This overlay scheme is a fundamental approach in color fusion. An example is given in fig.1: Taken two MRI scans image from the overlaying schemes is transfer into a single image, but at the cost of reduced image contrast (e.g., in the temporal lope and cerebellum as indicated by the white circles).In this paper, we propose a fusion rule that blends the pixel valves in the monochrome source image to combine information, while preserving or enhancing contrast.Image fusion method has three different levels. They are pixel/data level, feature/attribute level, and symbol/decision level, each level have different purpose, compared with the other pixel-level fusion directly combines the original information in the source images and is more computationally efficient. According to whether multi-scale decomposition (MSD) is used, pixel-level fusion methods can be classified as MSD-based or non-MSD based. Compared to the latter, MSD-based

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methods have the advantage of extracting and combining salientfeatures at different scales, and therefore normally produce images with greater information content. The general block diagram of MSD-based fusion is illustrated in fig: 2.First read image or source images are given to multi-scale representation (MSRs) using MSD. An MSR is a pyramidal structure with successively reduced spatial resolution; it contains one approximation level (APX) storing Low-pass co-efficient and several data level (DETs) storing High-pass or band pass co-efficient, then apply a certain fusion rule to merge co-efficient) is ge

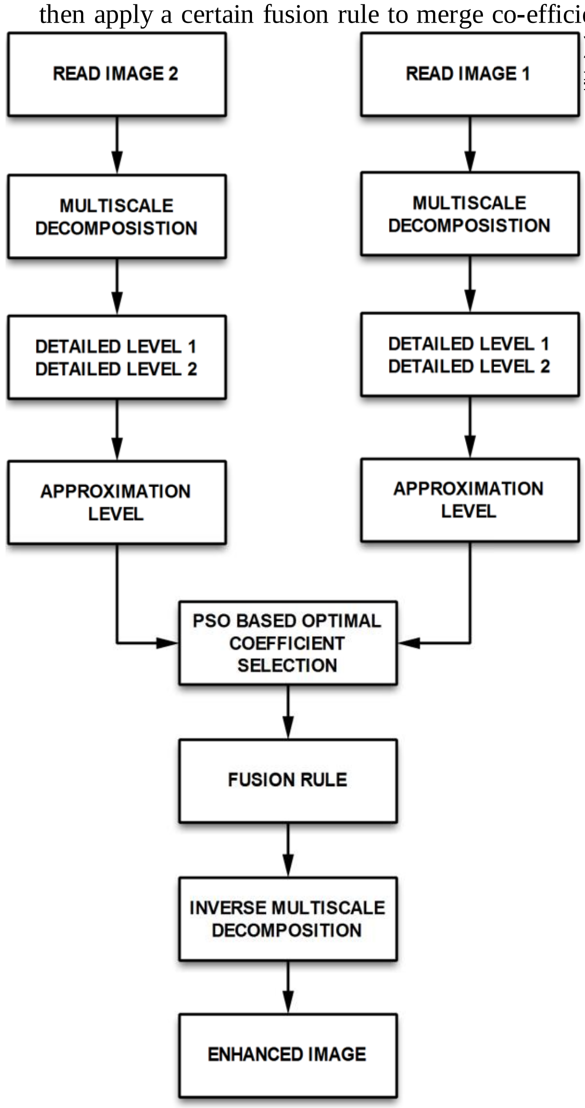

Fig.:2.General block diagram of PSO Based

To describe a technique for image encoding in which local operators of many scales but identical shape serve as the basis functions. The representation differs from established techniques in that the code elements are localized in spatial frequency as well as in space. Pixel-to-pixel correlations are first removed by subtracting a low-pass filtered copy of the image from the image itself. The result is a net data compression since the difference, or error, image has low variance and entropy, and the low-pass filtered image may represented at reduced sample density. It was not efficient. A method of producing red-green and blue-yellow sinusoidal chromatic gratings is used which permits the correction of all chromatic aberrations. A quantitative criterion is adopted to choose the intensity match of the two coolers in the stimulus: this is the intensity ratio at which contrast sensitivity for the chromatic grating differs most from the contrast sensitivity for a monochromatic luminance grating, It was less sensitivity. To describe an apparatus and methodology to support real-time color imaging for night operations. Registered imagery obtained in the visible through near-infrared band is combined with thermal infrared imagery by using principles of biological opponent-color vision. Visible imagery is obtained with a Gen In this III image intensifier tube fiber-optically coupled to a conventional charge-coupled device (CCD), and thermal infrared imagery is obtained by using an un cooled thermal imaging array. The two fields of view are matched and imaged through a dichroic beam splitter to produce realistic color renderings of a variety of night scenes. False alarm rate was higher. The fusion of three-dimensional (3-D) ultra-sound (US) and magnetic resonance imaging (MRI) data sets, without the assistance of external fiducially markers or external position sensors. Fusion of these two modalities combines real-time 3-D ultrasound scans of soft tissue with the larger anatomical framework from MRI. We describe the data acquisition, specialized algorithms. Disadvantage

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was Low performance and exact image planes for follow up comparisons over time (weeks, months, years) is difficult and may contribute to volume size errors.Grobner methods are used to design orthogonal filters with a sub-set of exactly symmetric coefficients of various lengths, as opposed to nearly symmetric. It was not robust to noise. To fuse a color visual image and a corresponding IR image for such a concealed weapon detection application. The fused image obtained by the proposed algorithm will maintain the high resolution of the visual image, incorporate any concealed weapons detected by the IR sensor, and keep the natural color of the visual image.it was less accuracy

3. SYSTEM MODELS

A. Particle Swarm optimization:

Particle swarm optimization is one of the evolutionary computation techniques. The method has been developed through simulation of simplified social models. PSO learns from scenario and uses it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles. PSO is initialized with a group [of random particles (solutions) and then searches for optima by updating generations. In each iteration, every particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. This value is called pbest. Another best value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called lbest.

B. Features Present in PSO Algorithm:

1. The method is based on researches in swarms such as fish schooling and bird flocking.
2. It is based on a simple concept. The computation time is short & it requires little memory.
3. Developed for nonlinear optimization problems with continuous variables

According to research results for bird flocking, birds find food by flocking (not by each individual). It leads to assumption that the information is shared in flocking. According to observation of behavior of human group, behavior of each individual (agent) is also based on behavior patterns authorized by the groups such as customs and other behavior patterns according to the experiences by each individual. Assumption is the basic concept of PSO. PSO is developed through simulation of bird flocking in two dimensional spaces. The position of each agent is represented by XY axis position and the velocity is expressed by vx. Modification of the agent position is realized by the position and velocity information.

1. Bird flocking optimizes a certain objective function.2. Each agent knows its best value (pbest) so far and best value in the group (gbest).3. Each agent tries to modify its position using the current velocity and the distance from the pbest& gbest.4. PSO utilizes several searching points like GA & the searching points gradually get close to the global optimum using its pbest&gbest

C. Flow Chart:

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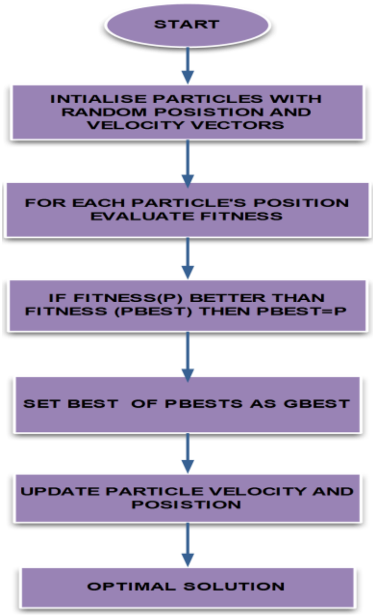

Fig: 2…flow chart in PSO algorithm

PSO utilizes several searching points like GA and the searching points gradually get close to the global optimum point using its pbest and gbest. The features of the searching procedures can be summarized as follows:

1) Initial positions of pbest and gbest are different. However, using the different directions of pbest and gbest, all agents gradually get close to the global optimum.2) The modified value of agent position is continues and the method can be applied to the continues problem.3) There is no inconsistency in searching procedures even if continuous and discrete state variables are utilized. 4) The concept can be easily applied to n dimensional problem.

PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. The detailed information will be given in following sections. Compared to GA, the advantages of PSO are that PSO is easy to implement and there are few parameters to adjust. PSO has been successfully applied in many areas: function optimization, artificial neural network training, fuzzy system control, and other areas where GA can be applied.The Particle Swarm Optimization algorithm is a biologically-inspired algorithm motivated by a social analogy. Sometimes it is related to the Evolutionary Computation (EC) techniques, basically with Genetic Algorithms (GA) and Evolutionary Strategies (ES), but there are significant differences with those techniques. The PSO algorithm is population-based: a set of potential solutions evolves to approach a convenient solution (or set of solutions) for a problem. Being an optimization method, the aim is finding the global optimum of a real-valued function (fitness function) defined in a given space (search space). The social metaphor that led to this algorithm can be summarized as follows: the individuals that are part of a society hold an opinion that is part of a "belief space" (the search space) shared by every possible individual. Individuals may modify this "opinion state" based on three factors: 1.The knowledge of the environment (its fitness value). 2. The individual's previous history of states (its memory). 3. The previous history of states of the individual's neighborhood. An individual's neighborhood may be defined in several ways, configuring somehow the "social network" of the individual. Several neighborhood topologies exist (full, ring, star, etc.) depending on whether an individual interacts with all, some, or only one of the rest of the population. Following certain rules of interaction, the individuals in the population adapt their scheme of belief to the ones that are more successful among their social network. Over the time, a culture arises, in which the individuals hold opinions that are closely related

D. Basic PSO algorithm:

In the PSO algorithm each individual is called a "particle", and is subject to a movement in a multidimensional space that represents the belief space. Particles have memory, thus retaining part of their previous state. There is no restriction for particles to share the same point in belief space, but in any case their individuality is preserved. Each particle's movement is the composition of an initial random velocity and two randomly weighted influences: individuality, the tendency to return to the particle's best previous position, and sociality, the tendency to move towards the neighborhood's best previous position. As stated before, PSO simulates the behaviors of bird flocking. Suppose the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But they know how far the food is in each iteration. So what's the best strategy to find the food? The effective one is to follow the bird which is nearest the food. PSO learned from the scenario and used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles,

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called lbest.

E. Comparisons between Genetic Algorithm and PSO Algorithm:

Most of evolutionary techniques have the following procedure:

1.Random generation of an initial population

2.Reckoning of a fitness value for each subject. It will directly depend on the distance to the optimum.

3. Reproduction of the population based on fitness values.

4. If requirements are met, then stop. Otherwise go back to 2. From the procedure, we can learn that PSO shares many common points with GA. Both algorithms start with a group of a randomly generated population, both have fitness values to evaluate the population. Both update the population and search for the optimum with random techniques. Both systems donotguarantee success. However, PSO does not have genetic operators like crossover and mutation. Particles update themselves with the internal velocity. They also have memory, which is important to the algorithm. Compared with genetic algorithms (GAs), the information sharing mechanism in PSO is significantly different. In GAs, chromosomes share information with each other. So the whole population moves like a one group towards an optimal area. In PSO, only gBest (or lBest) gives out the information to others. It is a one way information sharing mechanism. The evolution only looks for the best solution compared with GA, all the particles tend to converge to the best solution quickly even in the local version mostcases.

5. Artificial neural network and PSO:

An artificial neural network (ANN) is an analysis paradigm that is a simple model of the brain and the back-propagation algorithm is the one of the most popular method to train the artificial neural network. Recently there have been significant research efforts to apply evolutionary computation (EC) techniques for the purposes of evolving one or more aspects of artificial neural networks. Evolutionary computation methodologies have been applied to three main attributes of neural networks: network connection weights, network architecture (network topology, transfer function), and network learning algorithms. Most of the work involving the evolution of ANN has focused on the network weights and topological structure. Usually the weights and/or topological structure are encoded as a chromosome in GA. The selection of fitness function depends on the research goals. For a classification problem, the rate of mis-classified patterns can be viewed as the fitness value.

The advantage of the EC is that EC can be used in cases with non-differentiable PE transfer functions and no gradient information available. The disadvantages are 1. The performance is not competitive in some problems. 2. Representation of the weights is difficult and the genetic operators have to be carefully selected or developed. There are several papers reported using PSO to replace the back-propagation learning algorithm in ANN in the past several years. It showed PSO is a promising method to train ANN. It is faster and gets better results in most cases. It also avoids some of the problems GA met.

Here we show a simple example of evolving ANN with PSO. The problem is a benchmark function of classification problem: iris data set. Measurements of four attributes of iris flowers are provided in each data set record: sepal length, sepal width, petal length, and petal width. Fifty sets of measurements are present for each of three varieties of iris flowers, for a total of 150 records, or patterns. A 3-layer ANN is used to do the classification. There are 4 inputs and 3 outputs. So the input layer has 4 neurons and the output layer has 3 neurons. One can evolve the number of hidden neurons. However, for demonstration only, here we suppose the hidden layer has 6 neurons. We can evolve other parameters in the feed-forward network. Here we only evolve the network weights. So the particle will be a group of weights, there are 4*6+6*3 = 42 weights, so the particle consists of 42 real numbers. The range of weights can be set to [-100, 100] (this is just a example, in real cases, one might try different ranges). After encoding the particles, we need to determine the fitness function. For the classification problem, we feed all the patterns to the network whose weights is determined by the particle, get the outputs and compare it the standard outputs. Then we record the number of misclassified patterns as the fitness value of that particle. Now we can apply PSO to train the ANN to get lower number of misclassified patterns as possible. There are not many parameters in PSO need to be adjusted. We only need to adjust the number of hidden layers and the range of the weights to get better results in different trials.

F. PSO parameter control:

From the above case, we can learn that there are two key steps when applying PSO to optimization problems: the representation of the solution and the fitness function. One of the advantages of PSO is that PSO take real numbers as particles. It is not like GA, which needs to change to binary encoding, or special genetic operators have to be used. For example, we try to find the solution for f(x) = x1^2 + x2^2+x3^2, the particle can be set as (x1, x2, x3), and fitness function is f(x). Then we can use the standard procedure to find the optimum. The searching is a repeat process, and the stop criteria are that the maximum iteration number is reached or the minimum error condition is satisfied. There are not many parameter need to be tuned in PSO. Here is a list of the parameters and their typical values.

***The number of particles*:**
The typical range is 20 **-** 40. Actually for most of the problems 10 particles is large enough to get good results. For some difficult or special problems, one can try 100 or 200 particles.
Dimension of particles:
It is determined by the problem to be optimized.
Range of particles:
It is also determined by the problem to be optimized, you can specify different ranges for different dimension of particles.
Vmax: It determines the maximum change one particle can take during one iteration, usually we set the range of the particle as the Vmax for example, the Tparticle (x1, x2, x3 X1 belongs [-10, 10], then Vmax = 20.

Learning factors: c1 and c2 usually equal to 2. However, other settings were also used in different papers. But usually c1 equals to c2 and ranges from[0,4]

The stop condition:The maximum number of iterations the PSO execute and the minimum error requirement. for example, for ANN training in previous section, we can set the minimum error requirement is one miss-classified pattern. The maximum number of iterations is set to 2000. This stop condition depends on the problem to be optimized.

***Global version vs. local version*:** We introduced two versions of PSO, global and local version. Global version is faster but might converge to local optimum for some problems, local version is a little bit slower but not easy to be trapped into local optimum. One can use global version to get quick result and use local version to refine the search.

4.EXPERIMENTAL RESULTS AND DISCUSSION

A.Receiver operating characteristic (ROC):

Receiver operating characteristic (ROC) curves are useful for assessing the accuracy of predictions. Making predictions has become an essential part of every business enterprise and scientific field of inquiry. A simple example that has irreversibly penetrated daily life is the weather forecast. The example is concerned with the field of medical diagnostics. The word "prediction" rarely appears in this literature, but a diagnosis is a prediction of what might be wrong with a patient producing the symptoms and the complaints. Most disease processes elicit a response that is manifested in the form of increased levels of a substance in the blood or urine. There might be other reasons for such elevated levels, and blood or urine levels mis-diagnose a condition because of this. The kind of analysis one would perform for weather forecasts is similarly valid for these blood or urine "markers."ROC curves provide a comprehensive and visually attractive way to summarize the accuracy of predictions. They are widely applicable, regardless of the source of predictions. The field of ROC curves is by and large ignored during statistics education and training. Most statisticians learn of ROC curves on the jog, as needed, and struggle through some of the unusual features. To make matters worse for SAS users, very few direct methods are available for performing an ROC analysis although many procedures can be tailored with little attempt to produce ROC curves.There is also a macro available

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from the SAS Institute for this purpose. The goal of this paper is to summarize theavailable features in SAS for ROC curves and expand on using other procedures for further analyses.

Forecast	Observed		
	Frost	No Frost	Total
Frost	29	6	35
No Frost	4	38	42
Total	33	44	77

B. Basic concepts in binary predictor:

The simplest scenarios for prediction are the case of a binary predictor. It is important, not only pedagogically because it contains the most important building blocks of an ROC curve, but also practically because it is often encountered practice. I will use an example from weather forecasting to illustrate the concepts and at the end of the section mention some situations from other prominent fields. The article by Thornes and Stephenson (2001) reviews the concepts of assessment of predictive accuracy from the perspective of weather forecast products. Their opening example is very simple and accessible to all data analysts regardless of their training in meteorological sciences. The example relates to frost forecasts produced for M62motorway between Leeds and Hull in United Kingdom during the winter of 1995/1996. A frost is defined as when the road temperature falls below 0 °C. First, the forecast for each night is produced as a binary indicator Frost or No Frost. Then actual surface temperature for the road is monitored throughout the night and the outcome is recorded as Frost if the temperature dropped below 0 °C and as No Frost if it did not drop below 0 °C. The guidelines provided by the Highways Agency mandate the reporting of results (both forecast and the actual) in a consolidated manner (such as the following 2x2 contingency table) only for the days for which the actual temperature was below 5 °C. The example was concerned with the winter of 1995-1996 when there were 77 nights when the actual road surface temperature was below 5 °C. The results are given Table 1. Such a tabular description is the standard way of reporting accuracy when both the prediction and the outcome are binary. It is visually appealing, simple to navigate and it contains all the necessary information. There were 29 nights when frost was forecast and a frost was observed and there were 38 nights when no frost was forecast and no frost were observed. Those two cells (the diagonal cells of the 2x2 table, the shaded portion of Table 1) represent the two types of correct forecast. A general terminology is true positives (TP) and true negatives (TN). The roots of this terminology can be found in medical diagnostic studies when a test is called positive if it shows disease and negative if it does not show disease. By analogy we can consider frost to mean "positive" and no frost to mean "negative" in which case we will have 29 true positives and 38 true negatives.

Forecast	Observed		
	Positive	Negative	Total
Positive	True Positive (TP)	False Positive (FP)	TP+FP
Negative	False Negative (FN)	True Negative (TN)	FN+TN
Total	TP+FN	FP+TN	TP+FP+FN+TN

Table1:Forecast accuracy for road surface temperature

There are a variety of ways that one can summarize the forecast accuracy. One that comes to my mind first, perhaps, is the misclassification rate (MR) which is the proportion of all misclassified nights, the sum of false negative and false positives, out of all nights.

Table2:Reporting accuracy for binary predictions:

$$MR = \frac{FN + FP}{TP + FP + FN + TN}$$

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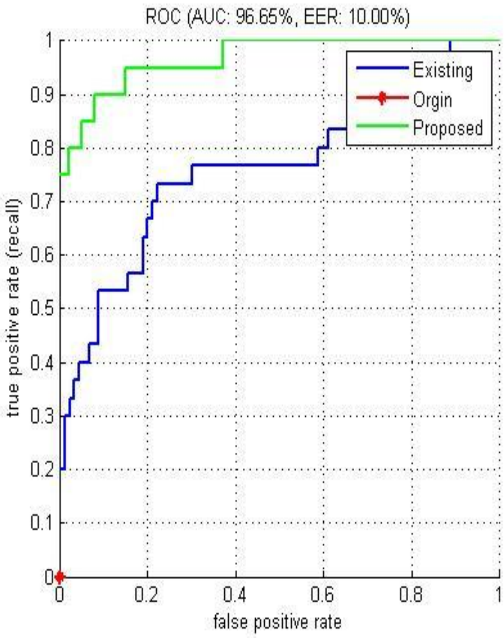
One minus the misclassification rate is sometimes called "percent correct" or simply "accuracy."Comparison between existing system and proposed system, when comparing both the accuracy is improved in the proposed system. So the quality of the proposed image is good, compared to existing system.

Fig3: Comparison waveform in exiting system and proposed system.



5. CONCLUSION

In this project, we proposed a multimodel image fusion algorithm based in multiresolution transform and particle swarm optimization(PSO). Firstly, the images are decomposed into low-frequency coefficients and high-frequency coefficients by the discrete cosine transforms(DCT) and the discrete wavelet transform (DWT). Then, the high-frequency coefficients are fused.The low-frequency coefficients are fused by weighted average method based on regions, and the weights are estimated by the PSO to gain optimal fused images. Experiments on volumetric medical image fusion demonstrated the effective-ness and versatility of our fusion rule, which produced fused images with higher quality than existing rules

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