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X-RAY IMAGE ENHANCEMENT USING CUCKOO ALGORITHM

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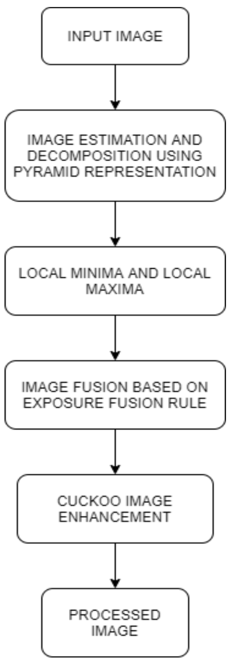
Abstract – *Due to an X-ray's low dynamic range and low contrast, vital aspects such as bones, nodules and organs become problematic to recognize. Henceforth, adjustment of the contrast is critical, particularly in view of its ability to enhance the details in both dark and bright areas of the image. For X-ray image enhancement, we therefore propose a new concept based on component attenuation, image fusion and cuckoo algorithm. Here we have assumed X-ray image could be disintegrated into tissue components and important details. Since tissues may not be major primary purpose of an X-ray. We proposed enhancing the visual contrast by separating the local minima and local maxima of the image and decomposing it via pyramidal representation later the obtained results are fused together using Exposure fusion.*

Key Words: X-ray imaging, Image enhancement, Pyramidal representation, Component attenuation, Cuckoo algorithm, Image fusion.

1. INTRODUCTION

X-Ray's assist doctors in determining what specific ailments are affecting their patients. Usually, X-rays are most frequently used to identify broken bones the reason being that the breaks and fractures appear clearly in X-Ray images, letting doctors to eliminate the possibility of strains or sprains. Patient's symptoms sometimes point to more than one possible problem or diagnosis. Using electromagnetic radiation technology literally gives doctors the X-ray vision they need in order to see exactly what is going on inside the human body. It is a fast, painless and non-invasive procedure that allows doctors to make correct and accurate diagnoses. Almost all meta-heuristics practice some form of stochastic components and try to reproduce the best features in nature, particularly biological systems. The selection of fitness and adaptation to the environment are crucial characteristics that the meta-heuristic algorithms attained. Direct method is mainly established considering two aspects which are the objective function and constraints. This method is slow and needs numerous function evaluations for convergence. Gradient-based method which has been established by considering the 1st or 2nd order derivative of the objective function (OF) and/or constraints for supervising the search process. This method leads to an ideal solution having considerably less efficiency in discontinuous problems or non-differentiable. In order to overcome the drawbacks of this method, the researchers develop the meta-heuristic algorithms to resolve the engineering optimization problems. Meta-heuristic algorithms have many methods, such as: simulated annealing (SA), Genetic algorithms (GA), Cuckoo Search (CS), particle swarm optimization (PSO), Firefly algorithms (FA),etc. The CS algorithms has obtained great interests and is found to be proficient. The CS algorithm is constructed on the significant breeding behavior such as brood parasitism of substantial Cuckoo species which is been considered as a new meta-heuristic algorithm for solving problems where major optimization is necessary. It is inspired by the necessitate brood parasitism of some Cuckoo species laying their eggs in the other host bird's nest during their breeding. The Cuckoos can be engaged by several host birds due to the Cuckoos intruding their nests. In the CS algorithm, each egg is considered to be a new optimal solution to replace less optimal solutions in the nest. This algorithm merged with another key feature called image fusion using exposure fusion technique to obtain better results.

2. PROPOSED SYSTEM



1. Flow or our approach

The design of the Cuckoo image enhancement technique consists of 4 stages. The first stage is the input stage where image input is taken as such. The second stage is the estimation of local maximum and local minimum of the input image using pyramidal representation. The third stage is the image fusion using exposure fusion technique where the separated images in the previous stage gets fused. The fourth stage is the Cuckoo enhancement where the Cuckoo algorithm is applied to the fused image formed in the previous stage. The final stage is where the output is received.

2.1. CUCKOO SEARCH ALGORITHM

Cuckoo search algorithm is predicated on the brood parasitism of some cuckoo species. Cuckoo birds lay their eggs within the nests of other host birds (usually other species) with amazing abilities like selecting nests containing recently laid eggs and removing existing eggs to extend the hatching probability of their own eggs. Some of the host birds are ready to combat this parasitic behavior of cuckoos and throw out the discovered alien eggs or build a replacement nest during a distinct location. This cuckoo breeding analogy is employed to develop the CS algorithm. Natural systems are complex, and therefore they cannot be modelled exactly by a computer algorithm in its basic form. Simplification of natural systems is important for successful implementation in computer algorithms. Yang and Deb simplified the cuckoo reproduction process into three idealized rules

A. An egg represents an answer and is stored during a nest. An artificial cuckoo can lay just one egg at a time.

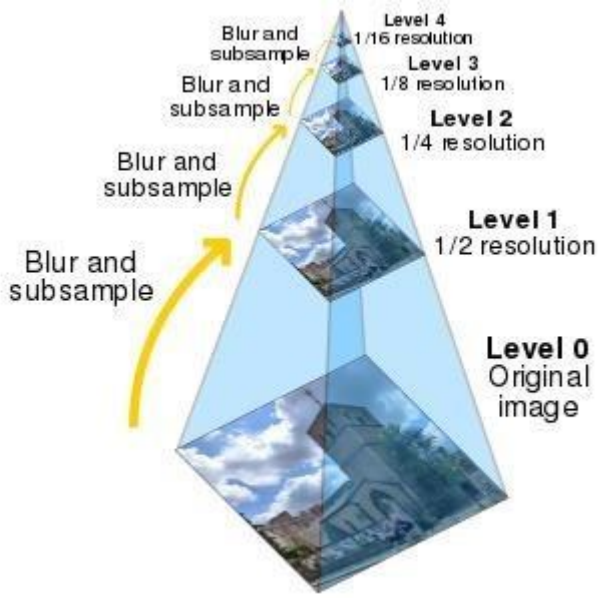
B. The cuckoo bird searches for the foremost suitable nest to get the eggs in (solution) to maximize its eggs' survival rate. An elitist selection strategy is applied, in order that only high-quality eggs (best solutions near the optimal value) which are more almost like the host bird's eggs have the chance to develop (next generation) and become mature cuckoos.

C. The number of host nests (population) is fixed. The host bird can discover the alien egg (worse solutions away from the optimal value) with a probability of pa[0,1] completely new nest is built in a new location. Otherwise, the egg matures and lives to subsequent generation. New eggs (solutions) laid by a cuckoo choose the nest by Lévy flights round the current best solutions.

From the implementation point of view, within the CS operation, a population, of eggs (individuals) is evolved from the initial point to a complete gen number iteration. Each egg represents an dimensional vector where each dimension corresponds to a choice variable of the optimization problem to be solved. The quality of each egg (candidate solution) is evaluated by using an objective function whose final result represents the fitness value of three different operators which define the evolution process of CS: (A) Lévy flight, (B) replacement of some nests by constructing new solutions and (C) elitist selection strategy

2.2 Pyramid Representation

It is a kind of multi-scale signal representation created by utilizing image processing, signal processing and computer vision communities, during which a picture or a sign is subject to repeated subsampling and smoothing. Eventually Pyramid representation is a predecessor to multi resolution analysis and scale-space representation.



2. Visual representation of an image pyramid with 5 levels

There are two main kinds of pyramids: lowpass and bandpass: A lowpass pyramid is made by smoothing the image with an appropriate smoothing filter then subsampling the smoothed image, usually by an element of two along each coordinate direction. The resulting image is then subjected to an equivalent procedure, and therefore the cycle is repeated multiple times. Each cycle of this process results in a smaller image with decreased spatial sampling density (which is, decreased resolution in the image), but with increased smoothing. If illustrated graphically, the whole multi-scale representation will appear as if a pyramid, with the first image on rock bottom and every cycle's resulting smaller image stacked one atop the opposite. A bandpass pyramid is formed by forming the difference between images at adjacent levels within the pyramid and performing some quite image interpolation between adjacent levels of resolution, to enable computation of pixelwise differences[4][7].

A variety of various smoothing kernels are proposed for generating pyramids. Among the suggestions that are given, the binomial kernels we obtain from the binomial coefficients stand out as a theoretically well-formed and very useful class. Therefore, assumed a two-dimensional image, we might apply the (normalized) binomial filter (1/4, 1/2, 1/4) typically twice or more along each spatial dimension which is then subsampled by a factor of two. This operation may then proceed as repeatedly as desired, resulting in an efficient and compact multi-scale representation. If motivated by specific requirements, intermediate scale levels can also be generated where the subsampling stage is usually overlooked, resulting in an oversampled or hybrid pyramid. with the increasing computational efficiency of CPUs available today, it's in some situations also feasible to use wider support Gaussian filters as smoothing kernels within the pyramid generation steps.

A. Gaussian pyramid

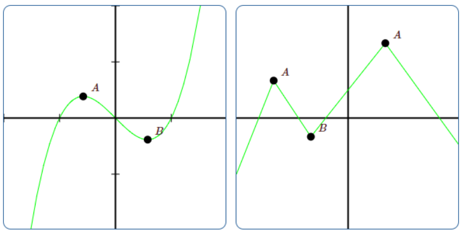
In a Gaussian pyramid, subsequent images are laden employing a Gaussian average (Gaussian blur) and scaled down. Each pixel containing an area average corresponds to an area pixel on a lower level of the pyramid. This technique is used especially in texture synthesis.

B. Laplacian pyramid

A Laplacian pyramid is extremely almost like a Gaussian pyramid but saves the difference image of the blurred versions between each level. Only the littlest level isn't a difference image to enable reconstruction of the high-resolution image using the difference images on higher levels. This technique can be used in image compression.

2.3. ESTIMATION OF LOCAL MAXIMA AND MINIMA

Let us consider that the local maximum point at a function can be any point (x,y) on the graph of the function whose y coordinate can be larger than all the other y coordinates on the graph at points which are nearest to (x,y). More precisely, (x,f(x)) may be a local maximum if there's an interval (a,b) with a<x<b and f(x)≥f(z) for every z in (a,b). Similarly, (x,y) is a local minimum point if it has locally the smallest y coordinate. Again being moreprecise: (x,f(x)) is a local minimum if there is an interval (a,b) with a<x<b and f(x)≤f(z) for every z in (a,b)[7].



3.Some local maximum points (A) and maximum points (B).

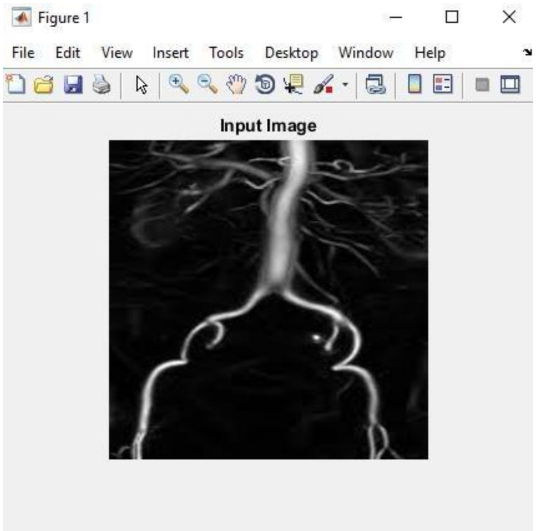
A local extreme point is either a local maximum or a local minimum. Local minimum and maximum points are basically distinctive on the graph of a function, and because of which they are useful in understanding the form of the graph. In many applied problems we would like to seek out the smallest or largest value that a function achieves (for example, we'd want to seek out the minimum time at which a thread can be performed) and so identifying maximum and minimum points will be useful for applied problems as well. Couple of examples for the local minimum and maximum points are displayed in figure 3

2.4. IMAGE FUSION USING EXPOSURE FUSION

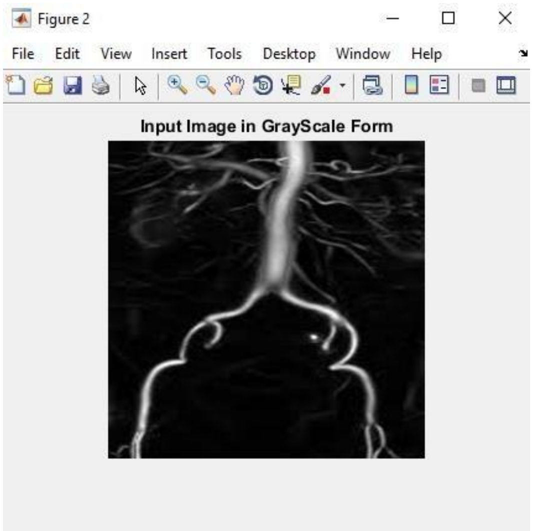
In image processing, special effects, and photography, exposure fusion may be a technique for blending multiple exposures of an equivalent scene (bracketing) into one image[8]. As in high dynamic range imaging (HDRI or simply HDR), the goal is to capture a scene with a better dynamic range than the camera is capable of capturing with a single exposure. By using several different exposure parameters on an equivalent scene, which are merged into a picture with better dynamic range after a wider dynamic range regularly being represented. After correcting for shifts that may evidently happen with hand-held devices, the full-image can be fused in two different methods. A higher dynamic range raw image is often reassembled and tone- mapped like usual HDR images, or more commonly: A blended image are often directly produced without reconstructing a better bit-depth [8]. The methods which were used previously assumes a linear response from the camera device, which can be provided by DNG or any raw formats. Few of the methods can take developed images, even though the method of reconstructing the intensities is complicated and noisy, consisting of the effective dynamic range. The latter method [Mertens-Kautz-Van Reeth (MKVr)] only cares about aligning features and taking the simplest parts, automatically (by contrast, saturation, and well-exposedness) or manually, so it's resistant to this drawback. However, it can't be considered a real HDR technique because no HDR image is ever created. The image does look better on displays, but the resulting bit depth of the image is adequate to the input depth, unlike on a real HDR image where a superior bit depth permits storing more detailed intensity changes. This methods strength has always been its ability to be flexible, this method is usually stretched to accomplish focus stacking by using contrast because of the sole criteria.

3. EXPERIMENTAL RESULTS

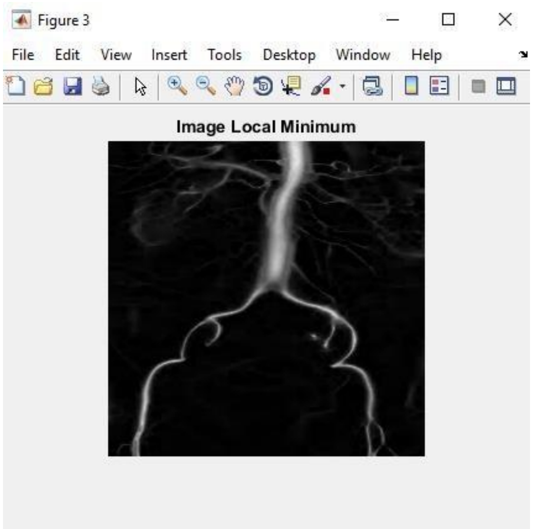
Here the various steps involved in image enhancement by applying multiple methods discussed earlier have been applied to the given image and the processed images and shown as experimental results. Each step of the image enhancement are displayed.



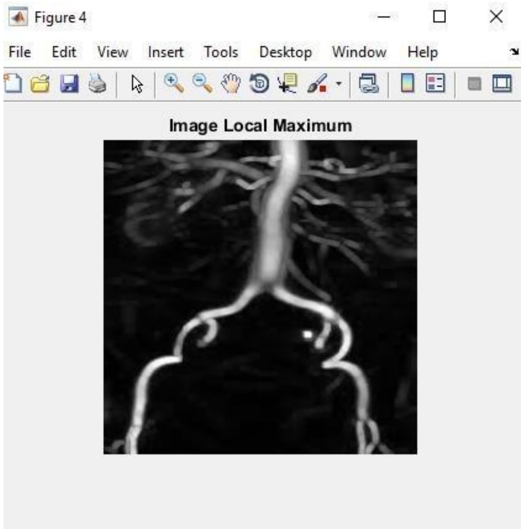
4. Input Image



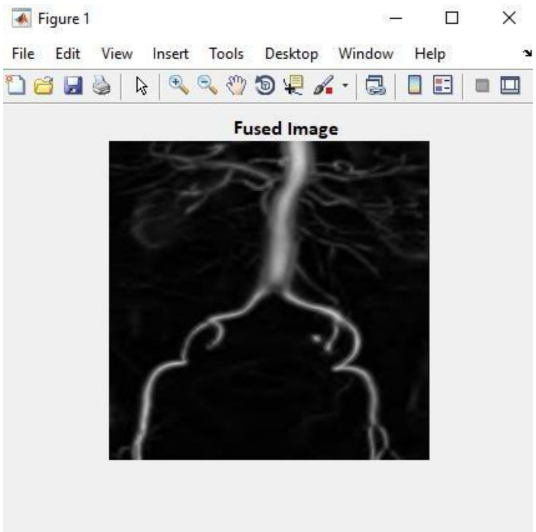
5. Image in Grayscale Form



6. Local Minimum Image



7. Local Maximum Image



8. Fused Image

4. CONCLUSIONS

The energy recorded in an X-ray image is in a position to reveal the interior condition of a person's body. Thus, X-ray imaging has become a standard tool for health inspection. However, the low contrast property of an X-ray image makes it hard to recognize tiny and abnormal details. In out proposed system a new enhancement system based on component attenuation (using Pyramidal representation), image fusion (using exposure fusion) and cuckoo optimization algorithm was implemented. By attenuating the tissues over the image, we can enhance the essential details in both the bright and dark regions adaptively. The model enables users to easily enhance image contrast by adjusting the attenuation scale and by applying cuckoo algorithm to the obtained results. We have used four measurement metrics and a dataset to evaluate our system. The results demonstrated the effectiveness of our method to enhance organs, bone structure, and some small but significant details, such as tiny nodules in low contrast X-ray images.

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