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Literature Review on Image Enhancement Technique in Medical Image Processing

Priyadarshini Chatterjee
Assistant Professor, Department of Information Technology, Hyderabad, Andhra Pradesh, India

Abstract:
Image Enhancement is a process to improve the quality of an image for further processing required for a specific purpose. Improving the quality of an X-ray image and the image taken of Mars has a different approach. One of the major problems in medical image is their poor contrast quality and noise. Some of the common forms of medical images that are generally dealt with are TRUS (Trans-rectal Ultrasound), MRI (Magnetic Resonance Imaging) and X-Rays. Other than the usual image enhancement technique, this paper deals with the analysis of anisotropic diffusion and topological derivative as the major tools of medical image enhancement techniques. Anisotropic diffusion is broadly based on selective smoothness or enhancement of local features such as region boundaries. If the image under analysis is subjected to any hole or crack, topological derivative helps us to quantify the sensitivity of the problem.

Keywords: Image enhancement, anisotropic diffusion, topological derivative.

1. Introduction

Medical Images like MRI, CT (Computed Tomography) etc provide us with a detailed 3-D study of the internal organs [1], [7] [8], [9]. Various kinds of information are extracted from these images subject to the organs under examination. As these images are usually affected by noise and poor contrast, if not enhanced properly the concluding results will be inaccurate. The area of medical imaging is perturbed with this problem. The solution is to reduce the noise while preserving the details of the image. The extent to which blurring has to be done should be under control. Many studies are done on noise removal and edge preserving methods. All these methods are well known but briefly discussing them will help to differentiate how anisotropic diffusion and topological derivative is better than these methods and more application oriented.
Important denoising methods are:

1.1. Median Filtering
As image filtering is broadly classified as linear and nonlinear of which median filtering is of type non linear [1]. It is an effective method to reduce noise (especially salt and pepper noises) and also preserve the edges. The median filter moves through the pixels of the image replacing each value with the neighboring pixels. The area (made up of pixels) surrounding the concerned pixel is called a window. The median is calculated by sorting all the pixels in the window in numerical order and replacing the pixel under consideration with the median value of the sorted pixels in the window.

1.2. Hybrid Median Filtering
Images are to some extent corrupted by Impulse noise. Impulse noises occur in an image due to transmission errors, malfunctioning of the camera pixels, faulty memory locations and other such factors. Impulse noises are classified in two major types:
   a) Salt and pepper noise: impulse values are represented as numerical values in the range of 0 and 255. The salt and pepper noise have equal height of impulses.
   b) Random-Valued Impulse Noise: These types of noises have unequal height of impulses.
 These Hybrid median filters are non linear class of windowed filters which removes noise after preserving the edges. The unique feature of hybrid median filtering is its corner preserving characteristics. The principle of working of the hybrid median filter is by constantly altering the window shape and taking the median of the calculated median values and applying on the pixel under consideration. The hybrid median takes two medians: in an "X" and in a "+" centered on the pixel. The output is the median of these two medians and the original pixel value.
 The commonly used edge-preserving methods are the Bayesian Estimate, the Maximum Likelihood (ML) that helps us to analyze the concerned image more clearly from a corrupted image (that contains Gaussian Noise). Giving a brief about each of the following techniques:

1.3. Bayesian Estimate
Bayesian Estimation takes into consideration the prior knowledge of the situation under study [6], [7]. Bayesian Estimation technique is based on Posterior Probability that says that the degree of one's certainty is based on a given situation. According to Bay's law, the posterior probability is proportional to the product of likelihood and the prior probability. Likelihood means the information present in the new data and prior probability gives us the degree of certainty concerning the situation before the data is taken. Posterior Probability mainly describes the state of certainty of any possible image, but Bayesian Estimation proceeds by taking into consideration a single image that maximizes the posterior probability. This type of estimate is also called MAP estimate. Choosing the prior is critical in this method which makes it unique from the other methods.

1.4. Summary of Posterior Probability and Priors
Let x be the parameter on which we wish to improve our knowledge. We perform some experiments and collect some data d. the present state of certainty is characterized by the probability density function *p(x).* The joint probability density function is given by the equation

$$P(x,y)=p(y|x)p(x) \dots\dots\dots\dots\dots\dots\dots\dots \textbf{(1)}$$

Substituting d for y in the above equation and solving it both the ways (keeping both an and y fixed one at a time) we get the Bay's Law as

$$p(x|d) = p(d|x) \, p(x) \dots\dots\dots\dots\dots\dots\dots\dots\textbf{(2)}$$
$$p(d)$$

We call *p(x|d)* as the posterior probability density function as it effectively follows the   experiment. It is the conditional probability of x given the new data d. The probability   density function *p(x)* is called prior as it represents state of knowledge before the experiment. The term *p(d|x)* is called likelihood as it expresses the probability of data d given any particular x.

2. Choice of Estimator
We need to express *p(x|d)* in a more concise term as it contains more information than is required. The critical point is that making cost analysis as the basis the Bayesian approach provides an optimal way to interpret the posterior probability. To achieve optimality, we also need to consider the various costs (risks) associated with the kind of errors in the estimation process.
A standard measure of the accuracy of the result is the variance (mean square error). The expected variance of a parameter $\hat{x}$ is

$$\int \ p(x|d) \ | \ x- \ \hat{x} \ |^2 \ dx \ \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\textbf{(3)}$$

It can be shown that the estimator that minimizes the posterior probability density function is

$$\hat{x} = \bar{x} = \int \ xp(x|d) \ dx \dots\dots\dots\dots\dots\dots\dots\dots\dots\textbf{(4)}$$

2.1. Use of These Parameters in Image Analysis

2.2.1. Posterior Probability
Given the data g, the posterior probability of any image f in terms of the proportionality can be expressed as

$$p(f|g) \propto p(g|f)p(f) \dots\dots\dots\dots\dots\dots\dots\dots\dots\textbf{(5)}$$

The negative logarithm of the posterior probabi\lity density function is given by

$$-\log[p(f|g)] = \Phi(f)=\Lambda(f)+\pi(f)\dots\dots\dots\dots\dots\dots\dots\dots\textbf{(6)}$$

In the above equation the first term comes from the likelihood and the second term from the prior probability.
        Priors
A Gaussian density function is used for the prior whose negative logarithmic term may be written in simplified form as

$$-\log[p(f)] = \pi(f) = 1/2\sigma_f^2|f- \bar{f} \ |^2\dots\dots\dots\dots\dots\dots\dots\dots\textbf{(7)}$$

The MAP estimate is a solution to the set of linear equation

$$\blacktriangledown_{f\Phi = -1} /\sigma_n^2 \ H^T(g-Hf) + 1/ \sigma_f^2(\ f- \bar{f} \ )=0\dots\dots\dots\dots\dots\dots\textbf{(8)}$$

These equations are rearranged to express the solution for 'f' in terms of simple matrix   operation. The properties of this solution in the use of image reconstruction shed light on the general characteristics of the MAP solution. The use of priori known constraints, such as non negativity along with Gaussian prior has shown benefits for reconstruction from limited data.

2.2. Maximum Likelihood Estimation
This is mainly used for the image contrast enhancement. Image contrast is the difference between the visual property of the object that distinguishes it from another object and the back ground of the image. Contrast property helps the human eye to locate the noticeable differences in an image [8].
In the context of image processing a single mode distribution for text and a multi-mode for back ground are usually used. Normally a Gaussian model is used for each mode in these distributions. Distributions are considered as highly local and we take the back ground

distribution of a pixel as a single mode one. The question is how to model the behavior of an image and background information in features space. Two simple basic models can be used to model each of them.

    i)   Histogram Based Model
    ii) Gaussian Model

In Histogram based model each class is estimated according to its probability density function. The Maximum Likelihood Estimation is given by

$$\mu_{ml}(x) = \arg \text{Max}\{f(x|\mu)\} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \textbf{(9)}$$

where

$$f(x|\mu) = f(x_1|\mu), f(x_2|\mu), \ldots f(x_n|\mu) \textbf{................................(10)}$$

is the likelihood function. The maximum likelihood estimation of µ is obtained as the solution to

$$(\eth/\eth\mu)f(x|\mu)\mu = \mu_{ml=0}\text{..}\textbf{(11)} \text{ and}$$

$$(\eth^2/\eth^2 u)f(x|\mu) \mu = \mu_{ml=0 <0}\text{..}\textbf{(12)}$$

The goal of MLE is to binarize the image and separate them from the background and possible interfering patterns.
Other edge-preserving methods include Markov Random Field (MRF) based method where the posterior conditional probability is maximized that is later used to restore the image. There is also adaptive smoothing filter based method that is used to denoise an image preserving the edges. The pixel intensities is used as a measure for discontinuities.
Apart from the above mentioned methods, I would like to elaborate on two methods Anisotropic Diffusion suggested by Perona and Malik and Topological derivatives basically used to enhance a medical image.

2.3. Anisotropic Diffusion
This method deals with scale-space description of images and edge detection [3],[4]. The main use of diffusion in image processing is to remove noise using a partial differential equation (PDE). The heat equation or isotropic diffusion equation is given by

$$\eth_u/\eth_t = \text{div}(k\blacktriangledown_u)\text{................................}\textbf{(13)}$$

where u = u(x,y,t) the coordinates of the image that is being enhanced in the continuum domain at an instant t. The input image is given by u(x,y,0) as the initial condition for the above equation. The pair of coordinates (x,y) specifies a spatial position in the image and t is the time parameter. Application of this equation to the input image is similar to applying a Gaussian filter that produces a blurring effect and reduces the sharpness of the image edges.
In this approach suggested by Perona and Malik, an anisotropic coefficient k(x) is used to "stop" the diffusion over the edges of the image:

$$\eth_u/\eth_t = \text{div}(k(x)\blacktriangledown_u)\text{..}\textbf{(14)}$$

The function k(x) is chosen to satisfy that k->0 as x->α, so as to stop the diffusion process in the presence of large gradients. As per Perona and Malik k(x) should be

$$K(x, K) = 1/(1 + x^2/k^2)\textbf{................................(15)}$$

where K is appositive constant. There are different ways to compute the value of k(x). For example if a noisy image needs to be enhanced, preserving the image boundaries and reducing as much noise as possible then k can be k =k($\blacktriangledown_u$). So an alternative considering only two possible values of k was studied, where k € {0, 1}.
There is another variation of anisotropic diffusion model which is called as detail –preserving anisotropic diffusion model that is used for image restoration. This model not only preserves the edges of an image but also retains the fine details while smoothing noise in an image. It does so by smoothing the non-uniform background and noisy region in the sensed image. It is seen that the neighbor hood of the inter region edges generally has both high gradient magnitudes and high gray level variances. In order to preserve fine details after removing noise, both the gray-level variance and gradient are considered as two local pixel features.
If we take (x, y) as the coordinate as the coordinate of the image pixel at iteration t, the gray level variance is calculated from its 3×3 neighborhood, i.e.

$$\eth_1{}^2(x, y) = 1/9 \sum_{i=-1}^{1} \sum_{j-1}^{1} [I_1(x + i, y + j) - \bar{I}(x, y)]^2\text{....................}\textbf{(16)}$$

where $\bar{I}(x, y)$ is the mean of gray levels in the 3×3 neighborhood window. After incorporating both local features of gray-level variance and gradient in the diffusion process, the diffusion coefficient function is revised as

$$g(\blacktriangledown I{}^i{}_t(x, y), \sigma^2{}_{t,N}(x,y)) = 1/[1+(\frac{\blacktriangledown I{}^i{}_t(x, y), \sigma^2{}_{t,N}(x,y)}{k_0})^2]\text{................}\textbf{(17)}$$

where k_0 is a positive constant used as an edge strength threshold. So the revised diffusion model is given by the equation

$$I_{t+1}(x,y) = I_t(x,y) + 1/4 \sum_{i=1}^{4} [g(\blacktriangledown I{}^i{}_t(x,y), \sigma^2{}_{t,N}(x,y)) . \blacktriangledown I{}^i{}_t(x,y)]\text{............}\textbf{(18)}$$

If $\sigma^2_{t,N}$ (x ,y) is fixed throughout the entire image, $\sigma^2_{t,N}$ / k_0 will become a constant and the equation 17 above will become the P-M diffusion model.

2.4. Topological Derivative
Topological derivative is mainly used for segmentation in image analysis that helps us to identify major tissues and organs of patient specific data [2]. Topological derivative is used to quantify the cost associated with the segmentation of image data. It also helps us to quantify the sensitivity of a problem when the concerned image is perturbed by the heterogeneity of the surrounding.
If classical image segmentation techniques are used then basic approaches are used i.e. discontinuities and similarities. These basic approaches are not suitable for the images that are surrounded by other image structure of similar image intensity. Other image segmentation approaches like the use of Level Sets though give good results but have high computational costs
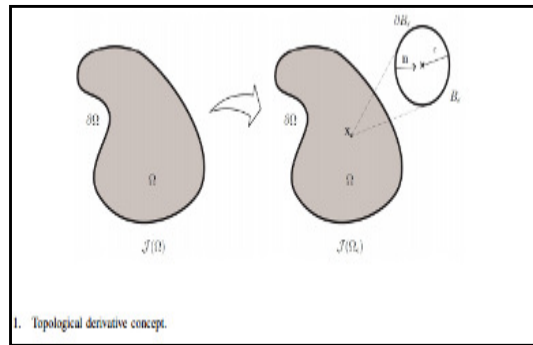

1. Topological derivative concept.

Figure 1: Main Concept of Topological Derivative

The image data can be considered as a two dimensional matrix of pixels or three dimensional matrix of voxels (image element) [5]. Each of the image elements has associated image intensity. So, the original image data can be a real valued function v that is constant at image element level:

$$v \in V = \{ w \in L^2(\pi) ; w \text{ is constant at image element level}\}\text{...............}(19)$$

Let C be the set of os classes, such that

$$C = \{c_i \in R ; i = 1,...., N_c\}\text{...}(20)$$

Where N_c is the number of predefined classes in which the original image v is segmented in which c_i represents the intensity that characterizes the i_{th}-class.
So as per Topological derivative image segmentation can be defined as, as the image data v € V, a segmented image u* € U exists that minimizes a function J: U->R that is associated as the cost of specific segmented image in which U is defined as:

$$U = \{u \in V: u(x) \in C, \forall_x \in \pi\}\text{..}(21)$$

The following cost function J associated to a segmented image u € U is given as;

$$J(\pi) = 1/2 \int_\pi K \blacktriangledown_\Phi . \blacktriangledown_\Phi d\pi + 1/2 \int_\pi (\Phi-(v-u))^2 d\pi\text{.............................}(22)$$

where Φ is the solution of the following problem. Associated with Φ is defined the function Φ_ϵ that is the solution of a perturbed variation formulation. Therefore, as per this model the perturbed cost functional become

$$J(\pi_\epsilon) = 1/2 \int_\pi K \blacktriangledown_{\Phi\epsilon} . \blacktriangledown_{\Phi\epsilon} d\pi + 1/2 \int_\pi (\Phi_\epsilon-(v-u_T))^2 d\pi\text{.......................}(23)$$

So applying topological derivative on domain under consideration π is non uniform as of a hole, an inclusion of a term in a small region B_ϵ (where B_ϵ is a ball of radius ϵ), the topological derivative derived from the equation basic equation

$$J(\pi_\epsilon) = J(\pi) + f(\epsilon) D_T(\hat{x}) + o(f(\epsilon))\text{...}(24)$$

Can be redefined as an integral defined on the boundary of the ball $\eth B_\epsilon$ as:

$$D_T(\hat{x}) = -\lim_{\epsilon \to 0} 1/f'(\epsilon) \int_{\eth B\epsilon}\left(\sum_\epsilon^e - \sum_\epsilon^i \right) n. n\text{.............................}(25)$$

3. Conclusion
Simple spatial averaging over neighboring pixels reduces the noise signal amplitude but degrades sharp features and produces a blurring effect. This effect can be reduced by using non-linear filters. Even median filters have the ability to retain borders, but image details are lost. So the Anisotropic Diffusion by P. Perona and J. Malik enhances an image keeping the boundaries intact and blurring the image to the extent necessary. The topological derivates helps to quantify the problem if the image is perturbed by any hole. It helps in segmenting those images that are surrounded by similar images of same characteristics and thus helps us to analyze the image more vividly. Topological Derivatives are basically used to optimize any problem and has shown excellent results as and when applied to image segmentation in the domain of image processing.

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