### 3.2 Subset inserted attack

This kind of attack also called mix-and-match attack. It is very similar to subsetting selection attack on tuples. The comparison show that our technique is resilient to selected attack. While on the other hand, the old technique deteriorates just after adding 10% of the data set size. Figure 5 shows the resilience of our watermarking technique to insertion attack, where the watermark was recovered with 100% accuracy even when up to 40% of the data set size tuples were inserted.

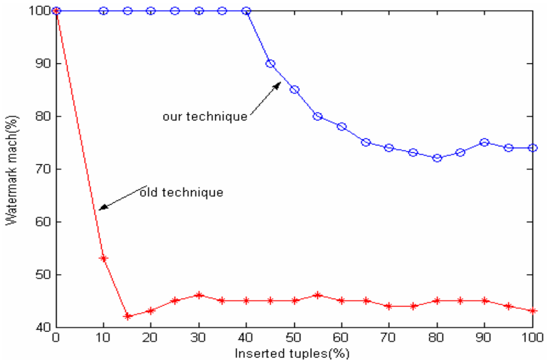


**Figure 5. Compare our with old watermark technique**

### 3.3 Alteration attack

In this form of attack, Violators try to alter some attribute values of relational database which had watermarked, and stochastically alter the attribute values. Suppose that attacker magically knows the values of the $v$ and $\xi$ parameters used by database owner. Since attacker does not know which bits have been marked, he randomly selects a Bernoulli ($\kappa$) sample from the n tuples. For each selected tuple, he flips all of the bits in all $\xi$ bit positions in all $v$ attributes.

To be noted, the robustness of our algorithm has close relation with marking frequency. The higher marking frequency we get, the more robust it is. Yet a compromise between robustness and imperceptibility must be reached in implementary phase. Figure 6 shows the experimental results; they clearly show that our watermarking technique is resilient to the random modify attack.

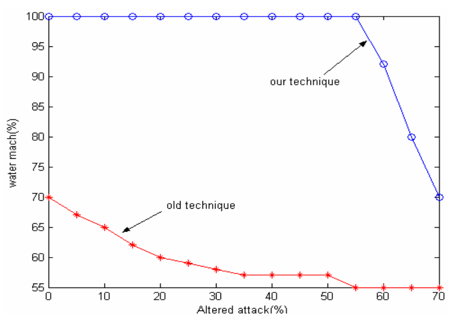


**Figure 6. Compare our with old watermark technique**

## 4 CONCLUSIONS

In this paper, we study the numeric attributes digit watermark technology in relational database. Watermark signal coding and water embedding were formulated as a constrained optimization problem. The results verify the effectiveness and usefulness of our approach. Furthermore, comparing with existing proposals, it also implies the superiority of our approach over the previous ones. We have presented a resilient watermarking technique for relational data that embeds watermark bits in the data statistics. The algorithm proved to have immunity to popular attacks to relational databases and need the smallest available bandwidth. Further work, we intend to conduct research on improving the robust of the scheme by the GA technology.

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# Research of Edge Detection Based on B-Spline multi-scale Wavelet Transform

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**Abstract:** Multi-scale analysis of wavelet transform solves noise suppression and edge extraction of conflict between the details well. Wavelet transform has the ability to detect local mutations. And signal edge is where the greatest rate of change. So wavelet transform is a good tool for edge detection. B-Spline function is chosen as the wavelet smoothing filter operators. This approach excels in the filter will also remove some weak edges. In order to compensate for this deficiency, an improved B-Spline wavelet edge detection algorithm with adaptive threshold is proposed. According to the computer simulation, this algorithm has a good anti-noise performance and edge localization ability, maintains the weak edge together with noise elimination.

**Keywords:** Wavelet Transform; B-Spline Wavelet; Multi-scale Analysis; Adaptive Threshold

# 基于B样条的多尺度小波变换边缘检测研究

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**摘 要：**小波变换的多尺度分析较好的解决了噪声抑制与边缘细节提取之间的矛盾。并且具有检测局域突变的能力，因此小波变换是检测边缘的良好工具。由 B 样条函数构成的平滑滤波算子在滤波的同时能够去掉一些弱的边缘的，采用多尺度自适应的 B 样条小波边缘检测算法对图像边缘进行提取。仿真实验验证表明，本文算法具有很好的抗噪性能和边缘定位能力，在实现消噪的同时，能很好的保留微弱边缘。

**关键词:**小波变换；B 样条小波；多尺度分析；自适应阈值

## 1 引言

目前，在边缘检测技术领域，许多边缘提取方法在工程、工业生产、农业、军事、医学以及科学研究等各个领域中，已经得到了广泛的应用。比如说医学影像的降噪、农产品的外观品质检测等。这些方法提高了边缘检测的性能，具有较好的应用前景。尽管如此，但图像的边缘提取问题并没有得到比较完善的解决：边缘灰度变化的减少，使得边缘提取出现了一定困难；图像在生产和传输过程中产生的噪声，使得边缘提取存在伪边缘、漏检测边缘等现象；受拍摄环境和条件的限制，图像中总会有一些与目标无关的干扰存在等。如何提高边缘检测的准确性，使边缘提取算法具有更高的信噪比是图像处理的经典难题。所以好的边缘检测算法一直是众多学者研究的重点。

小波变换是近年来兴起的一种热门信号处理方法，它良好的时--频局部特性非常适合于图像处理，所以得到了广泛的应用。不同尺度下，图像灰度的急剧变化点的集合对应图像的边缘，即表现为信号的奇异性，这就要求在提取边缘时运用多尺度思想，很好解决了噪声抑制与图像边缘细节提取之间的矛盾。而小波对图像信号的多分尺度分析非常适合检测信号的奇异性，所以小波是图像边缘检测的一种有力工具[1, 2]。

## 2 小波变换的多尺度分析和奇异性的关系

小波变换的多尺度分析[3, 4]是建立在函数空间概念上的理论，这套理论的建立为正交小波基的构造提供了一种简单方法，为正交小波变换的快速算法提供了理论依据，因此多尺度分析在正交小波变换理论中具有非常重要的地位。

为了避免小尺度下的伪极值点和大尺度下的定位偏差，我们在用小波变换模极大值检测信号突变点时，需要把多尺度结合起来观察。若函数中某处有间断或某阶导数不存在，则称该函数中此处有奇异性，该点

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就为函数的奇异点。数学上，函数的奇异性通常用Lipschitz（李氏）指数$\alpha$来描述[5]。

我们假设小波函数$\psi(t)$是连续可微的，并且在无限远处的衰减速率为$O(\frac{1}{1+t^2})$。Mallat[6,7]证明：当$t$在区间$[a,b]$中时，如果$f(t)$的小波变换满足：

$$|W_a f(t)| \le k a^{\alpha} \qquad (1)$$

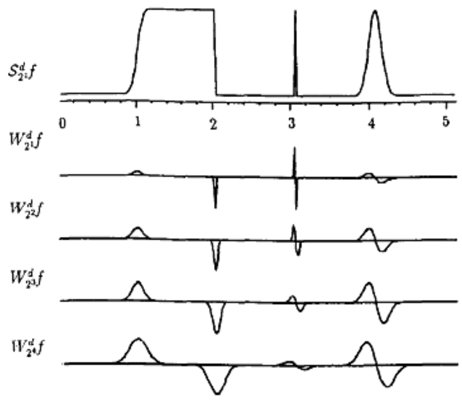
也就是 $\log|W_a f(t)| \le \log k + \alpha \log a$

当$a = 2^j$时，上式变成：

$$|W_{2^j} f(t)| \le k(2^j)^{\alpha} \qquad (2)$$

或 $\log_2 |W_{2^j} f(t)| \le \log_2 k + j\alpha$

式中$j\alpha$这一项把小波变换的尺度特征$j$与 Lipschitz 指数$\alpha$联系了起来。



$$t=1, \alpha_0 = 0, \sigma = 3; t = 2, \alpha_0 = 0, \sigma = 0;$$
$$t=3, \alpha_0 = -1, \sigma = 0; t = 4, \alpha_0 = -1, \sigma = 3$$

**Figure 1. Wavelet transform extreme changes in scale**
**图1.小波变换极值随尺度的变化**

图1描述了几种突变点的小波变换模极值随尺度的变化规律，其中$t$在1、4处有正则点（非奇异点），在2处有一个阶跃函数，在3处有一个$\delta$函数。

## 3 B样条函数及算子

设n阶多项式样条生成的类空间记为$S_i^n$，这里上标n表示多项式的阶数，而下标$i$代表了结点间距离[8]。在每个区间上$S_i^n$等价于n阶多项式，可如下定义：

$$S_i^n = \left\{ f_i^n(t) = \sum_{k=-\infty}^{+\infty} C_i(k) \beta_{2^j}^n (t - 2^j k), C_i \in L^2 \right\} \qquad (3)$$

这里$C_i(k)$为B样条系数，$\beta_{2^j}^n(t) = \frac{1}{2^j}\beta^n(\frac{t}{2^j})$。基函数$\beta^n(t)$即是n次中心B样条函数，由n+1个0阶B样条经反复卷积而产生[8,9]：

$$\beta^n(t) = \beta^{n-1} * \beta^0(t) = \overbrace{\beta^0(t) * \beta^0(t) * \cdots * \beta^0(t)}^{n+1次}$$
$$= \beta^n(t) = \sum_{j=0}^{n+1} \frac{(-1)^j}{n!} \binom{n+1}{j} \left( t + \frac{n+1}{2} - j \right)_+^n \qquad (4)$$

其中$\beta^0(t) = \chi_{[-\frac{1}{2}, \frac{1}{2}]}$为区间$[-\frac{1}{2}, \frac{1}{2}]$上的特征函数。已知$\beta^n(t)$是非负的，而且B样条函数是同次样条函数空间中具有最小支撑的基底，其支集为$[-\frac{n+1}{2}, \frac{n+1}{2}]$。它的傅立叶变换为：

$$\hat{\beta}^n(\omega) = [\hat{\beta}^0(\omega)]^{n+1} = \left[ \frac{\sin(\omega/2)}{\omega/2} \right]^{n+1} = [\sin c(\frac{\omega}{2})]^{n+1} \qquad (5)$$

Mallat等人早已指出[7,10]使用平滑函数的一阶导数的极值检测优于使用其二阶导数的零交叉检测。所以我们取平滑函数的一阶导数作为边缘检测的小波即可。我们知道三次B样条函数对含噪数据是一种有效的平滑工具，并且在控制平滑级数时可以很好地权衡简单和高效之间的关系。且三次B样条函数的综合性能优于Gaussian函数[11]。所以最终确定用三次B样条函数来构造边缘检测的平滑滤波算子。

由公式4和公式5的反变换推出三次B样条函数：

$$\beta^3(t) = \begin{cases} (t+2)^3/6, & t \in [-2,-1) \\ -t^3/2 - t^2 + 2/3, & t \in [-1,0) \\ t^3/2 - t^2 + 2/3, & t \in [0,1) \\ (2-t)^3/6, & t \in [1,2) \\ 0, & 其它 \end{cases} \qquad (6)$$

所以得二次样条小波算子：

$$\psi(t) = \beta^{3'}(t) = \begin{cases} (t+2)^2/6, & t \in [-2,-1) \\ -3t^2/2 - 2t, & t \in [-1,0) \\ 3t^2/2 - 2t, & t \in [-1,0) \\ -(2-t)^2/2, & t \in [1,2) \\ 0, & 其它 \end{cases} \qquad (7)$$

二维图像的推广[9]：若二维函数$\beta^n(x,y)$的积分为零，则称其为二维平滑函数。令$\beta_s^n(x,y) = \frac{1}{s}\beta^n\left(\frac{x}{s}, \frac{y}{s}\right)$，则二维信号$f(x,y) \in L^2(R^2)$的平滑是通过在不同尺度$s$上与$\beta_s^n(x,y)$作卷积来实现的。若利用张量积，平滑函数和小波函数可取为：

$$\beta^n(x,y) = \beta^n(x)\beta^n(y) \qquad (8)$$

$$\begin{cases}\psi^{n,1}(x,y)=\psi(x)\xi(y)\\ \psi^{n,2}(x,y)=\xi(x)\psi(y)\end{cases} \tag{9}$$

这里要求 $\xi(t)=2\beta^{n}(2t)$。若，则这时平滑算子和小波变换分别定义成：

$$S_{2^j}f(x,y)=f*\frac{1}{2^j}\beta^{n}(\frac{x}{2^j},\frac{y}{2^j})=f*\beta^{n}_{2^j}(x,y) \tag{10}$$

和

$$W_{2^j}f(x,y)=\begin{bmatrix}W^1_{2^j}f(x,y)\\ W^2_{2^j}f(x,y)\end{bmatrix}=\begin{bmatrix}f*\psi^{n,1}_{2^j}(x,y)\\ f*\psi^{n,2}_{2^j}(x,y)\end{bmatrix} \tag{11}$$

容易证明

$$\begin{bmatrix}W^1_{2^j}f(x,y)\\ W^2_{2^j}f(x,y)\end{bmatrix}=2^j\begin{bmatrix}\frac{\partial}{\partial x}(f*\beta_{2^j})(x,y)\\ \frac{\partial}{\partial y}(f*\beta_{2^j})(x,y)\end{bmatrix}=2^j\nabla(f*\beta_{2^j})(x,y) \tag{12}$$

这时右端是平滑函数梯度的$2^j$倍，在尺度$2^j$上，梯度矢量的模正比于小波变换的模：

$$M_{2^j}f(x,y)=\sqrt{\left|W^1_{2^j}f(x,y)\right|^2+\left|W^2_{2^j}f(x,y)\right|^2} \tag{13}$$

梯度矢量与水平方向的夹角（相角）为：

$$A_{2^j}f(x,y)=\arctan\left[\frac{W^2_{2^j}f(x,y)}{W^1_{2^j}f(x,y)}\right] \tag{14}$$

在由角度 $A_{2^j}f(x,y)$ 提供的方向上，可以求出图像小波变换在各尺度的局部模极值，对应于图像中的边缘。

## 4 自适应阈值

为了除去由噪声和灰度不均匀所引起的虚假边缘，需对边缘图像设置一个阈值。对整幅图像若采用同一阈值，则在除去噪声的同时，图像中的微弱边缘也会被除去，从而影响到检测效果。所以我们采用小波多尺度自适应阈值[12]方法（即自适应分块法）对图像进行边缘检测。

自适应阈值计算公式如下：

$$T=T_0+a_0\times\sum_{i,j}C_{i,j} \tag{15}$$

其中，$T$是阈值，$T_0$是初始值，$C_{i,j}$是与当前窗口相对应的小波系数，$a_0$是一比例系数，用以决定与当前窗口相对应的小波系数对阈值的影响程度，$T_0$、$a_0$的值可根据实际情况调整。本文中$T_0$取为5，$a_0$取为0.001。

## 5 仿真检验

本文采用三次B样条的小波自适应阈值多尺度边缘检测算法对图像边缘进行了提取。

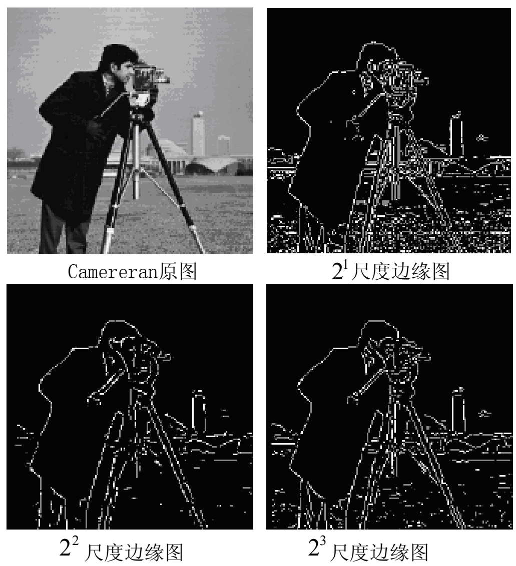
图2是选择对lenna图像进行多尺度边缘提取，分别在二尺度和三尺度上采用了固定阈值和自适应阈值两种方法。


**Figure2. Multi-scale extraction results with different threshold**
**图2 多尺度不同阈值的提取结果**

从图 2 的实验结果可以看出，自适应阈值相比固定阈值，较好地保留了微弱边缘。小尺度比大尺度在细节上更丰富一些。

图3选择对Cameraman原图及含噪图像进行多尺度图像边缘检测，结果如下所示，图中所用噪声是方差为0.05的椒盐（salt & pepper）噪声。

从图3可以看出：本文算法在小尺度下提取的边缘细节丰富，较好地保留了微弱边缘；而在大尺度下，边缘定位比较准确，具有很好的抗噪能力。所以本算法具有较好的抗噪性能和边缘定位能力，在实现消噪的同时，能较好的保留微弱边缘。



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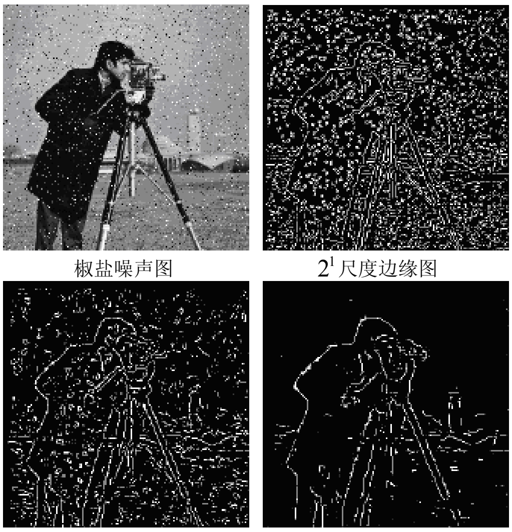


**Figure3. Different scale edge detection map**

**图3 不同尺度边缘提取图**

## 结束语

小波变换是一种多分辨率分析工具，为不同尺度上信号的分析和表征提供了精确和统一框架。当小波函数尺度较大时，抑制噪声能力增强，提取边缘细节的能力变差；当小波函数尺度较小时，抑制噪声能力变弱，但提取边缘细节的能力增强。这样很好解决了噪声抑制与图像边缘细节提取之间的矛盾。并且小波变换具有奇异性，而图像边缘正是信号变化率最大的地方，因此小波变换是检测边缘的一种良好的工具。基于三次 B 样条的小波自适应阈值多尺度边缘检测算法，在实现消噪的同时，能较好的保留微弱边缘。

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