Wavelet compression and segmentation of mammographic images

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ABSTRACT

Haar wavelets were used for the compression of mammographic images containing clustered microcalcifications. Fifteen mammograms with 105 μm/pixel resolution and varying dynamic range (10 and 12 bits per pixel) containing clustered microcalcifications were compressed with two different rates. The quality and content of the compressed reconstructed images were evaluated by an expert mammographer. The visualization of the cluster was on the average good but degraded with increasing compression due to the discontinuities introduced by these type of wavelets to the images as the compression rate increases. The artifacts, however, in the decoded images were seen as totally artificial and were not misinterpreted by the radiologist as calcifications. The classification of the parenchymal densities did not change significantly by the morphology of the calcifications was increasingly distorted as the compression rate increased leading to lower estimates of the suspiciousness of the cluster and higher uncertainties in the diagnosis. The uncompressed and two sets of compressed images were followed by a wavelet decomposition and reconstruction process to extract the calcifications. The algorithm successfully extracted the calcifications from the original images. However, the computerized segmentatic of the highly compressed data generates false positive spots which are distracting elements in the diagnosis. It seems that a universal approach may not be suitable for both compressed and uncompressed data or that the segmentation algorithm should be specially designed, if images of different resolution are to be processed with the same method and parameters.

Key words: wavelets, image compression, segmentation, mammography.
INTRODUCTION

Digital mammography involves either the digitization of screen-film mammograms or the direct digital acquisition of x-rays. In both cases, the requirements for high resolution images with high dynamic range lead to large data sets, on the average about 50 Mpixels with dynamic ranges of 12 bits per pixel. In addition, screening digital mammography implies real-time availability to the radiologist of a series of such images per patient for comparative study and accurate diagnosis. Such large image database challenges the existing technology for data storage, transmission, and display. Data compression methods could facilitate these processes but they should also satisfy the requirements for highly accurate reconstruction of mammograms.

Several lossless and lossy compression methods have been investigated for medical imaging applications. Lossless compression methods applied to mammography include tree-based codes which represent a large class of variable-length encoding schemes and arithmetic codes. Lossless methods have the advantage that they can be applied anywhere since such compressed images are reconstructed without error. Their disadvantage is the small compression rates, on the order of 3:1. In contrast, lossy techniques can achieve very high compression ratios at the expense of errors in the reconstructed images. A new class of lossy compression algorithms is currently under development which could offer data with no visible artifacts. Receiver operator characteristics (ROC) analysis on lossy compression showed that it is possible to use lossy techniques in medical imaging, provided that the diagnostic power is not lost or diminished. Such methods are referred to as "visually lossless" and hold promise for effective mammogram compression. The properties of the human visual system are such that some losses can be tolerated without affecting the visual evaluation of an image which, despite
the losses, appears identical to the original. Furthermore, even visually lossy images may be acceptable, when artifacts due to lossy compression can be recognized as entirely artificial and do not disturb the discriminating analysis followed by the radiologist to reach a diagnosis. Finally, it should be pointed out that the use of lossy compression methods depends on the application, the image, and the aims of a particular project.\textsuperscript{5}

One of the most promising lossy compression approaches uses wavelets.\textsuperscript{11} Wavelets have been already used for mammogram segmentation,\textsuperscript{12,13} enhancement,\textsuperscript{12} and compression.\textsuperscript{7} The present study focuses on the use of Haar wavelets for the compression of mammographic images containing clustered calcifications. Uncompressed and compressed reconstructed data were also processed with a segmentation algorithm that employed a wavelet transform. A radiologist expert in mammography evaluated the quality of the compressed images and the usefulness of the segmented data based on a questionnaire designed to provide a qualitative description of the original and compressed images. An ROC clinical evaluation is beyond the scope of this research since we are at the stage of optimizing the compression method and selecting the best approach for mammography. Therefore, the purpose of the study is three-fold: to apply different levels of compression to mammography and determine the limits of acceptable losses, to evaluate the quality of the compressed images and the effect of the losses in the radiologist’s diagnosis, and finally to demonstrate the feasibility of processing the uncompressed and compressed data with the same wavelet-based segmentation algorithm in order to extract the calcifications independent of the specific image or the design philosophy of the method.
MATERIALS AND METHODS

Mammograms

Fifteen screen-film mammograms were considered as a first test of the compression algorithm. They all contained one biopsy-proven malignant cluster of calcifications superimposed on parenchymal tissues of varying density. All mammograms were digitized at a resolution of 105 μm/pixel. Seven images had a dynamic range of 10 bits per pixel (1024 grey levels) and eight had a dynamic range of 12 bits per pixel (4096 grey levels). The optical density range selected for the digitization was different for each mammogram and it was determined from the optical density of the brightest spot on the films. This allowed the maximization of the intensity differences between the various breast features and thus maximum separation in pixel values between the microcalcifications and the surrounding tissues. Sections of the images (512x512 pixels) containing the calcification cluster were used for compression and segmentation. The sizes of the original images were 327,680 and 393,216 bytes for the 10-bit and 12-bit files respectively.

Image compression

A mathematical theory that analyzes the efficiency of wavelet-based image compression schemes is described in detail elsewhere. The method used in this study for the compression of mammographic images is identical to that used to report the results of Fig. 14 in reference 11 and only a brief description of the method will be presented here.
A wavelet-based compression algorithm is constituted of three steps. First, a wavelet family is selected that will be used to decompose the image. Each wavelet family has different smoothness characteristics and approximation properties; in this paper, the Haar wavelets are chosen based on our previous experience. Second, a quantization strategy must be selected. Each strategy is equivalent to a metric with which the difference between the original and reconstructed images will be measured. Two popular choices of metric are the $L^2$ (mean-square error) and $L^1$ (mean-absolute error) metrics. If the pixels of the original image $f$ are denoted by $p_j$, $j=(i, j_2)$ and $1 \leq i, j_2 \leq 512$, and the pixels of the reconstructed image $\hat{f}$ are denoted by $\hat{p}_j$, then the mean-square error is defined by

$$\|f - \hat{f}\|_2 := \left( \frac{1}{N} \sum_j |p_j - \hat{p}_j|^2 \right)^{1/2}$$

and the mean-absolute error is defined by

$$\|f - \hat{f}\|_1 := \frac{1}{N} \sum_j |p_j - \hat{p}_j|,$$

where $N$ is the number of pixels in the image; in this study $N=512 \times 512 = 262,144$. The quantization strategy determines the relative importance of contrast and spatial frequency in choosing which features of the image can be removed while causing minimal visual degradation.

It was previously reported that for $512 \times 512$ natural images viewed at a standard viewing distance of four times the width of the image, the contrast-frequency tradeoff implied by the $L^1$ error metric more closely matched the characteristics of the human visual system than the contrast-frequency tradeoff implied by the choice of the $L^2$ error metric. Mammograms are not
viewed by radiologists solely at arm’s length, however, and it was observed with earlier 8-bit
digitized mammograms that the $L^2$ metric balanced the degradation of the edges and shapes of
microcalcification clusters with the degradation of the structure of architectural distortions in the
underlying tissues. The $L^1$ quantization strategy at a given level of compression tended to
preserve the structure of architectural distortions better than the $L^2$ strategy, at the expense of
smoothing away evidence of microcalcifications. Therefore, for our first controlled study, we
chose to use only the $L^2$ quantization strategy. The results of this work will serve as guidelines
for our future investigations of other quantization strategies.

Third, after choosing the wavelets and quantization strategy, one must select a parameter
called the maximum quantization interval, $q$, which roughly determines the local error. The
greater the $q$ is, the greater the compression, but also the greater the error. When dealing with
images with different dynamic ranges (in this study, for example, seven of the images have 1024
grey levels and eight have 4096 grey levels), it is useful to consider the normalization of the
intensity range to a minimum of 0 and a maximum of 1. This can be done by dividing all pixel
values by the maximum grey scale value $2^K$, where $K=10$ or 12 in this study. Then, the
parameter that best estimates the local visual quality of the image is $q/2^K$. Thus, $q=512$ for our
12-bit images leads to comparable compression ratios and local image quality as $q=128$ for our
10-bit images. When comparing mean-square errors, it is again useful to divide by the maximum
grey scale. Thus, a mean-square error of 16 in a 10-bit image is roughly comparable to
mean-square error of 64 in a 12-bit image (or of 4 in an 8-bit image). Based on this reasoning,
fifteen mammograms were compressed twice with the parameters summarized in Table 1.

The compression algorithm was implemented in FORTRAN and C-language and run on
a Sun SPARCstation 2 and the time of compression was 10 sec per image.
Image segmentation

The uncompressed and compressed reconstructed images were processed as follows. First, the images were enhanced with a tree-structured nonlinear filter. As mentioned in detail elsewhere, this filter consists of a series of central weighted median filters which are applied to the image in three steps. This process allows effective suppression of the image noise without removing image detail. Second, the enhanced image was decomposed using a two-channel wavelet transform into four independent subimages which contain different types of frequencies. The first subimage contains the low frequencies of the image, the second contains the vertical high and horizontal low frequencies, the third contains the vertical low and horizontal high frequencies, and the fourth contains the high frequencies in both directions. Third, a wavelet reconstruction process was performed using the last three subimages resulting in one image which contains features corresponding to calcifications. Details of this algorithm are described elsewhere but it should be mentioned that the proposed wavelet segmentation could be further improved and optimized for compressed images.

Once the parameters of the segmentation algorithm are optimized for the uncompressed mammograms, they are kept constant for both uncompressed and compressed images. The software was written in C-language and run on a Sun Microsystems (Mountain View, CA) SPARCstation 2. The time of segmentation was about 5 min per image.

Evaluation protocol

A questionnaire was formed for the qualitative analysis of the original, compressed and
segmented images. It included nine questions shown in Table 2. Each question was rated on a scale of 1 to 5. A radiologist expert in mammography was asked to complete one questionnaire for each image although some of the questions were not applicable to all of them. There were 7 images to be evaluated per case, namely the film, the digitized image, the reconstructed image from the first compression, the reconstructed image from the second compression, and three segmentation results. The aim of this evaluation was to obtain a standard description of the visual characteristics of the quality of the digitized and compressed reconstructed images, to determine the degree of assistance of the segmentation algorithm to the recognition of the calcification clusters and have a first estimated of the acceptable limits for the lossy compression of mammograms.

Digital images were displayed on a 19" color Sun monitors with 1152x900 pixels using SunVision 1.2 software; no processing of the displayed images was permitted. It should be noted that current technology limits the display to 8 bits per pixel or 256 grey levels. With SunVision 1.2, the lowest values in the 10-bit or 12-bit images are scaled to 0, the highest values to 255, and the intervening values are scaled proportionately between 0 and 255; lower and higher values are clamped to 0 and 255 respectively.

RESULTS AND DISCUSSION

Figures 1 and 2 present sections of digitized mammograms (105 μm, 12 bits per pixel) before and after compression. The mammograms contain one cluster of biopsy-proven, malignant calcifications, the location of which is determined by an expert mammographer and is indicated by an arrow. There is a variation in the subtlety of the calcifications caused mainly by the
density of the surrounding or superimposed parenchymal tissues. The mammogram of Fig. 1(a) has a parenchymal density of about 50% and the mammogram of Fig. 2(a) has a density of about 75%. The compressed reconstructed images with a maximum quantization interval of 512 are shown in Figs. 1(b) and 2(b). Figures 1(c) and 2(c) show the corresponding compressed reconstructed images using a maximum quantization interval of 1024. Because of the differences in the parenchymal density and the noise content, different compression ratios and different mean-square errors were obtained for the same q value.

The results of the compression can be seen better in Figs. 3 and 4 where horizontal cross-sections through the calcification cluster of the images in Figs. 1 and 2 respectively are plotted. The continuity and smoothness of the pixels in the original images is increasingly lost as the maximum quantization interval and thus the compression rate increases. The higher compression ratio observed for the first mammogram is due to its lower parenchymal density which also accounts for the fact that the calcifications are better preserved in this case even at the higher compression (q=1024). On the other hand, the data are smoother in the second mammogram where smaller compression rates are obtained. In general, the compression effects are different for mammograms of low and high parenchymal densities. Furthermore, mammograms digitized at higher dynamic range (more grey scales) allow higher compressions with less information loss.

Table 3 lists the mean-square errors and the compression ratios achieved in the two compression sets. The compression ratios were determined by the number of bytes of the original files divided by the corresponding compressed sizes. It is best to interpret the mean-square errors by dividing by the number of grey scales in each image. Therefore, for the first compression results of Fig. 1(b), the mean-square error is $36.02/4096$ or 0.88% while for the second compression of Fig. 1(c), it is $45.46/4096$ or 1.11%. Similarly, the mean square errors
of the images in Figs. 2(b) and 2(c) are 13.54/1024 or 1.32% and 16.03/1024 or 1.56%.

Figures 5 and 6 show the segmentation results for the images in Figs. 1 and 2. The algorithm was successful in segmenting the calcifications from the uncompressed images. The loss of continuity and smoothness of the pixel in the compressed data affects the results of the segmentation algorithm in that it generates false positive spots which, although not of the same intensity as those corresponding to the calcifications, are considered as distracting by the radiologist, particularly for the higher compression (set #2). This indicates that either a different segmentation algorithm should be developed for compressed data or a different compression method should be used to avoid abrupt discontinuities in the compressed images. A solution to the latter can also be a different family of wavelets, currently under investigation, which would result in smoother images with smaller gradient.

It should be pointed out that the Haar wavelets used in this study are inherently non-smooth compression techniques and are expected to be discontinuous across lines that run vertically and horizontally. Thus, at very high compression ratios, the artifacts introduced into the compressed images consist of straight lines and corners where these lines intersect. Using smoother wavelets would introduce different artifacts. The Haar wavelet artifacts, however, have the advantage that they can be seen by the radiologist as totally artificial; indeed, there were no false positive readings of microcalcifications by the radiologist on the compressed images. On the other hand, the wavelet segmentation algorithm misread many of the edge artifacts as false positives, which made some of the compressed segmented images less useful to the radiologist as a tool for diagnosis. It remains to be seen whether the advantages of smoother wavelets (no edges in the reconstructed images) will outweigh the disadvantages (introducing artifacts that may be misread as microcalcifications or other structures).
The results of the evaluation of the visualization of the clustered calcifications are shown in Fig. 7 for the film, the uncompressed and the two sets of compressed data. In 60% of the films, the visualization of the cluster is classified as excellent; in 13% the visualization of the clusters is very good, and in 27% is good (Fig. 7(a)). The same 60% and 13% of excellent and very good cluster visualization respectively was obtained from the digitized uncompressed images (Fig. 7(b)). Only 8%, however, were classified as good while another 7% was classified as mediocre. The plots in Figs. 7(c) and 7(d) show that the first compression run with q=128 or 512 demonstrates 47% excellent visualization for compressions up to 53:1, 20% very good, 13% good, and 20% mediocre. The visualization degraded during the second compression run where the following percentages were calculated from the completed answer sheets: 13% excellent for compressions up to 56:1, 20% very good, 7% good, 33% mediocre, and 27% poor. It should be noted that the quality of the compressed data depends on the image contents, namely the parenchymal density and the image noise.

The radiologist’s estimates of the losses after compression led to the bar diagrams of Fig. 8. Losses included artifacts not present in the films, changes in the morphology of the cluster and the individual calcifications, and distortion of the breast parenchyma. Assuming no losses for the films, the losses in the digitized mammograms and the compressed images are graded on a scale of 1-5 from great to no losses. Scale #3 corresponded to average losses and was set as the limit of the acceptable level of losses for the purpose of this study. Figure 8(b) shows that only 13% of the first set of compressed images exceeded the average losses (grade #3). Furthermore, the major contribution to this percentage was from the 10-bit images. In contrast, 73% of the higher compression results exceeded the average losses.

The analysis of the remainder of the expert’s evaluation indicates the following. (a) In
90% of the cases, the number of calcifications estimated within a cluster is the same between the film, the digitized mammogram, and the first compression set and falls one range lower for the second compression set. (b) In 67% of the cases, the parenchyma density estimation and classification remains the same between the film, the digitized images, and the first compression set while a higher estimate is given for the second compression set. (c) In 33% of the cases, the same degree of suspiciousness of the lesion was given from the film, the digital mammogram and the compressed images. However, in the remaining 67%, the compressed data gave the impression of a less suspicious case than the originals. (d) The morphology of the calcifications (shape, size, and geometry) degrades in the entire second set of compression by one or two levels. 53% of the first compression data have similar morphology as the digitized mammograms and the corresponding films; the remaining 47%, the majority of which is from the 10-bit images, shows a one level degradation in the morphology of the calcifications. This also explains the differences in the suspiciousness of the cluster. (e) The digitized mammograms reproduce exactly the parenchyma patterns observed on the film. In 33% of the cases the first compression set did not show any visible distortion of the parenchymal tissues (4 out of these 5 cases were from the group of the 12-bit images). In all other cases the smoothness and continuity of the parenchymal tissues is gradually lost and the compressed data have a "boxy" appearance which increases with increasing compression ratio.

CONCLUSIONS

We have applied Haar wavelets for the compression of mammograms aiming at the highest possible compression with visually lossless or visually acceptable lossy data. Two high
compression rates were tested to determine the degree of losses and their effect on the visualization of malignant calcifications. Although the type of wavelets selected for this study introduce losses in the smoothness and continuity of the pixels in the original data, the visualization of the calcifications is rated as excellent for compressions up to 56:1. Furthermore, the expert mammographer could not discriminate the digitized from the decoded mammogram in 80% of the cases. The results, however, seem to depend on the contents of the original image and the dynamic range of the digital of the mammograms. It also appears that, despite the fact that the display of the images is limited by the current technology to 8 bits per pixel, decoded images with higher dynamic ranges were evaluated more favorably. Further studies are needed, however, if a digitization strategy more beneficial to the compression process is to be determined.

A wavelet segmentation algorithm was also applied to both uncompressed and compressed data. The results showed that the algorithm, at its present design, successfully segments the original image but generates false positive spots in the compressed data. Motivated by the results of the present study, we are now engaged in the implementation of smoother wavelet approaches for the compression of mammograms and the improvement of the wavelet segmentation algorithm in order to reduce the false positive detection rate in the data of high compression.
REFERENCES


Table 1: Parameters used for the two compression runs of the fifteen mammograms.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Set #1</th>
<th>Set #2</th>
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</thead>
<tbody>
<tr>
<td>Maximum quantization interval ( q )</td>
<td>128 - 10-bit images 512 - 12-bit images</td>
<td>256 - 10-bit images 1024 - 12-bit images</td>
</tr>
<tr>
<td>Space ( L^p )</td>
<td>( p=2 )</td>
<td>( p=2 )</td>
</tr>
</tbody>
</table>

Table 2. Questionnaire used for the qualitative evaluation of the compressed images and the segmentation data. One answer sheet was used for each image, namely the original film, the digitized mammogram, the compression #1, and the compression #2 although some of the questions were not applicable to all images.

<table>
<thead>
<tr>
<th>1. Visualization of calcification cluster</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>Excellent</th>
</tr>
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<tbody>
<tr>
<td>Poor</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Number of calcifications</td>
<td>1-5</td>
<td>6-10</td>
<td>11-20</td>
<td>21-30</td>
<td>&gt;30</td>
<td></td>
</tr>
<tr>
<td>3. Parenchyma classification</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>High</td>
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<tr>
<td>Low</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Degree of suspicion</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>Definitely Cancer</td>
</tr>
<tr>
<td>Definitely Normal</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Definitely Cancer</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>5. Distortion of calcifications' morphology</td>
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<td>6. Distortion of parenchyma</td>
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<td>5</td>
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<tr>
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<td>7. Degree of losses (overall)</td>
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<td>3</td>
<td>4</td>
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<td>8. Degree of confusion secondary to false positive artifacts</td>
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<td>9. Degree of assistance of segmentation process</td>
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Table 3. Dynamic ranges, mean-square errors measured in grey scales and compression ratios for the two compression sets which have different maximum quantization intervals.

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<tr>
<th>Image #</th>
<th>Grey levels</th>
<th>Mean-square error (set #1)</th>
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FIGURES

Figure 1.  (a) Section of digitized mammogram (105 μm, 12 bits per pixel) with a calcification cluster indicated by arrow. The cluster is embedded in parenchyma of low density, about 50%.  (b) Wavelet compressed and reconstructed image with maximum quantization interval q=512, mean-square error 37.14, and compression ratio 53:1.  (c) Wavelet compressed and reconstructed image with maximum quantization interval q=1024, mean-square error 48.99, and compression ratio 123:1.

Figure 2.  (a) Section of digitized mammogram (105 μm, 12 bits per pixel) with a calcification cluster indicated by arrow. The cluster is embedded in parenchyma of high density, about 75%.  (b) Wavelet compressed and reconstructed image with maximum quantization interval q=512, mean-square error 54.61, and compression ratio 22:1.  (c) Wavelet compressed and reconstructed image with maximum quantization interval q=1024, mean-square error 74.51, and compression ratio 55:1.

Figure 3.  Horizontal cross-sections through the calcification cluster shown in Figs. 1(a)–(c).  (a) Original uncompressed data, (b) compressed data with q=512, and (c) compressed data with q=1024.

Figure 4.  Horizontal cross-sections through the calcification cluster shown in Figs. 3(a)–(c).  (a) Original uncompressed data, (b) compressed data with q=512, and (c) compressed data with q=1024.

Figure 5.  Segmentation results of the images in Fig. 1 using two-channel wavelet decomposition and reconstruction.  Segmented calcifications from (a) original digitized image, (b) compressed data with q=512, and (c) compressed data with q=1024.

Figure 6.  Segmentation results of the images in Fig. 1 using two-channel wavelet decomposition and reconstruction.  Segmented calcifications from (a) original digitized image, (b) compressed data with q=512, and (c) compressed data with q=1024.

Figure 7.  Bar diagrams of the classification of the visualization of the calcifications in (a) the fifteen films, (b) the uncompressed digitized images, (c) the first set of compressed images, and (d) the second set of compressed images.  The scale is 1: poor, 2: mediocre, 3: good, 4: very good, 5: excellent.

Figure 8.  Bar diagrams of the grading of the overall losses in (a) the uncompressed digitized images, (b) the first set of compressed images, and (c) the second set of compressed images.  The scale is 1: great, 2: high, 3: average, 4: low, 5: none.
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