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An alternate method for using a visual discrimination model (VDM) to optimize soft-copy display image quality

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Abstract

Researchers have developed visual discrimination models (VDMs) that can predict a human observer's ability to detect a target object superposed on an image. These models incorporate sophisticated knowledge of the properties of the human visual system. In the predictive approach, termed conventional VDM usage, two input images with and without a target are analyzed by an algorithm that calculates a just-noticeable-difference (JND) index, which is taken as a measure of the detectability of the target. A new method of using the VDM is described, termed channelized VDM, which involves finding the linear combination of the VDM-generated channels (which are not used in conventional VDM analysis) that has optimal classification ability between normal and abnormal images. The classification ability can be measured using receiver operating characteristic (ROC) or two alternative forced choice (2AFC) experiments, and in special cases they can also be predicted by signal detection theory (SDT) based model-observer methods. In this study simulated background and nodule containing regions were used to validate the new method. It was found that the channelized VDM predictions were in excellent qualitative agreement with human-observer validated SDT predictions. Either VDM method (conventional or channelized) has potential applicability to soft-copy display optimization. An advantage of any VDM-based approach is that complex effects, such as visual masking, are automatically accounted for, which effects are usually not included in SDT-based methods.

Keywords

display optimization; image quality; just-noticeable-difference; visual discrimination model; VDM; signal detection theory; channelized observer; model-observers

INTRODUCTION

Researchers (1–3) have developed *visual discrimination models* (VDMs) that can predict a human observer's ability to detect a target superposed on an image. These models incorporate sophisticated knowledge of the properties of the human visual system. VDM algorithms require the input of a pair of luminance images, one with a lesion (or target) and the same image without a lesion. They calculate a number called a just-noticeable-difference (JND) index that is taken to reflect the detectability of the target. We use the term *conventional* VDM usage to describe this process. The precise definition of the JND-index will be given later but for now note that if the JND-index is large, then it is predicted that a human observer is able to easily detect the target. VDMs have received considerable attention(4–8) in the context of medical imaging since they have obvious applications to image quality optimization, including soft-copy display optimization (9,10). In the context of predicting medical image detection performance, one image of the pair is a lesion-free clinical image, and the other image is constructed by superimposing a simulated lesion on the same image. The method obviously requires the ability to simulate lesions in a realistic manner. The JND-index values are typically averaged over a set of images in order to obtain better statistics.

In this paper an alternate method of using the VDM algorithm is described that may also be used to optimize the image quality of a soft-copy display. The proposed method is termed the channelized VDM method. It involves finding the linear combination of the VDM generated channels (which are not used in conventional VDM analysis) that has optimal classification ability between normal and abnormal images. The normal – abnormal classification ability can be measured using receiver operating characteristic (ROC) (11,12) or two alternative forced choice (13) (2AFC) experiments, and in special cases they can also be predicted by signal detection theory (SDT) based model-observer methods (14). The procedure is related to ideas presented elsewhere (7,15) but differs in the manner in which the optimal linear combination is determined (the specific difference will be described below). In the following sections we describe the method, the validation procedure and present the results.

METHODS

The validation consisted of creating background regions on which to superpose nodules, and making measurements on the regions with and without the superposed nodules. Both clinical and simulated backgrounds were used. The former were extracted from normal regions of mammograms. The simulated backgrounds had statistically known noise characteristics. Targets with known shapes and sizes were superposed on the backgrounds. These images were used to validate the channelized VDM method.

Clinical Background Regions

A set of 146 normal mammograms was digitized at 12-bits per pixel at 100-micron resolution. Multiple non-overlapping 256 x 256 regions were extracted from each digitized image. The regions were chosen from parts of the breast with approximately constant thickness. The number of extracted regions per mammogram varied from 5 (for small breast images) to 38 (for large breast images). The total number of available clinical regions was 2405. The input values to the VDM program are required to be in luminance units. For each region the minimum and maximum pixel-values were determined and these were used to apply a standard linear look-up-table transformation to the pixels. The display driving level (DDL) values were converted to luminance values corresponding to a monitor calibrated according to the DICOM-14 standard for a maximum luminance of 300 Cd/m². This procedure resulted in regions with a mean luminance of 50.8 Cd/m² with a standard deviation of 36.0 Cd/m².

Simulated Background Regions

Spatially uncorrelated 256 x 256 Gaussian noise regions with pixel values in the range 0 to 255 (in units of Cd/m²) were generated by sampling a normal random number generator with mean 127 and a standard deviation 30. Sampled values outside the range were “clipped” to the allowed range. To generate correlated background regions we followed a published procedure (14,16). These regions had radial noise power spectra (NPS) with the following f (spatial frequency) dependence:

$$\text{NPS}(f) = \frac{\alpha}{f^\beta} \quad (f_0 < f < f_N), \quad (1)$$

where f_0 is lowest frequency that the image can support and f_N is the Nyquist frequency. This type of *power law noise* is characterized by two parameters. The α parameter is a scale factor that can be used to adjust the standard deviation of the noise region to a desired value (17). The β parameter, known as the *noise exponent*, determines how rapidly the noise power spectra increases as zero frequency is approached. For small β the increase is gradual and for large β it is sharper.

Fig. 1 shows examples of the different background regions used in this work. Shown are: (a) a nodule-free mammographic region, (b) an uncorrelated Gaussian noise region, and three simulated power law noise regions with different degrees of spatial correlation described by the β parameter, namely (c) $\beta = 1$, (d) $\beta = 2$ and (e) $\beta = 3$. Note the similarity of the mammogram-region (a) and the simulated region (e). This similarity and its consequences have been studied by others (14,18). The same random number seed was used to generate all simulated images shown in this example.

Simulated Nodules

Background regions were used to generate either normal ($T = 0$) or abnormal ($T = 1$) regions, where T is the truth index. If $T = 0$ the region was used unmodified as a normal region. If $T = 1$ the region was modified by superposing a nodule of specified size, shape and contrast at its center. Two types of circularly symmetric nodules were used in this analysis – Gaussian nodules and *designer nodules* (14,19,20). An abnormal region **A** (a 256×256 matrix) was calculated from a normal region **N** (also a 256×256 matrix) by the equation

$$A = N[1 + c s(r; R, \dots)], \quad (2)$$

where $s(r; R, \dots)$ is the nodule shape function, which is a function of r , the radial distance from the nodule center, the nodule radius R , and other nodule parameters to be specified. The constant c represents the peak contrast of the nodule. The nodule shape function was defined to have unit amplitude at the center of the nodule. The Gaussian nodule (GN) shape-function $s_{GN}(r; R)$ was defined by:

$$s_{GN}(r; R) = \exp\left(-\frac{r^2}{2R^2}\right). \quad (3)$$

The designer nodule (DN) shape function $s_{DN}(r; R, v)$ was defined by

$$s_{DN}(r; R, v) = \Pi(r/2R) \left(1 - \left(\frac{r}{R}\right)^2\right)^v, \quad (4)$$

where v is a constant, referred to as the *nodule exponent*, that characterizes the edge-sharpness of the nodule. For $v = 0$ the designer nodule function is a sharp “flat-top” disk of the type considered earlier (21). As v increases the nodule’s edge becomes more rounded. The step-function $\Pi(r/2R)$ ensures that the nodule does not extend beyond $r = R$, where $\Pi(x) = 1$ if $|x| < 0.5$ and is zero otherwise.

Conventional VDM Analysis

This analysis reflected the conventional usage of the VDM. The input values to the VDM program are required to be in luminance units. Therefore the luminance-transformed images, one with and one without the nodule, are provided as input to the algorithm, which calculates a just-noticeable-difference index j for the image pair. If the JND-index is large then the VDM predicts that a human observer should be able to readily discriminate between the two images. The quantitative relationship is

$$j = 2 \operatorname{erfinv}(2p - 1), \quad (5)$$

where “erfinv” is the inverse of the error function “erf” in (22) and p is the probability of correct discrimination of the image pair with JND-index = j .

Channelized VDM Analysis

Described below is the implementation of an idea outlined elsewhere (15). For each normal ($T = 0$) or abnormal ($T = 1$) region $\mathbf{R}$ we constructed the corresponding *uniform* region $\mathbf{U}$, in which all pixels had the same value, equal to the mean pixel value of the corresponding region. The regions $\mathbf{R}$ and $\mathbf{U}$ regarded as a pair were analyzed by the VDM software. The specific software used was “gcd11_1.exe” (version 9.10f, 04/2, obtained from Sarnoff Corporation). In addition to the JND-index the VDM program yielded additional information in the form of *channel files*, which are the result of a vision-model based decomposition of the image into cortex coefficients (23). The channel files will be indexed by the integer n , where $n = 1, 2, \dots, (8m + 1)$. For the specific VDM program used in this work there were 41 channel files and therefore $m = 5$. The number of channel files corresponds to the combinations of m spatial frequency channels and 8-orientation channels, each spanning 22.5 degrees, and an additional isotropic low-frequency channel. The channel outputs are represented by $\mathbf{X}$, which is an $(8m+1)$ element object, each component of which is an 8×8 array of real positive values. We refer to the VDM-derived process of calculating $\mathbf{X}$ from a region $\mathbf{R}$ as *channel decomposition* of the region $\mathbf{R}$. A similar process was applied to the target $\mathbf{T}$ superposed at 10% contrast on a noise-free background at luminance 127 Cd/m^2 . This yielded the vector $\mathbf{Y}$, which was also an $(8m+1)$ element object representing the channel decomposition of the target, termed the *template*. The $\mathbf{X}$ and $\mathbf{Y}$ objects were cross-correlated to calculate the channel outputs Ω , an $(8m+1)$ element array of scalars, as follows:

$$\Omega_n = \frac{\sum_{ij} X_{n;ij} Y_{n;ij}}{\sum_{ij} Y_{n;ij}}. \quad (6)$$

Here n is the channel number [$n = 1, 2, \dots, (8m+1)$] and i and j are integer indices ($i, j = 1, 2, \dots, 8$) that index the pixels in the 8×8 arrays. The idea of cross-correlation comes from signal detection theory according to which this operation yields an ideal observer in the detection task when the noise is “white”, i.e., uncorrelated. Specifically, the model observer used in this work is the *non-pre-whitening matched filter with zero frequency suppression*, which has seen applications in image quality measurements (24–29). In this manner we characterized each region by an $(8m+1)$ element vector Ω . The VDM program also provides a scalar JND-index for the pair of regions (i.e., a normal region and the same region with a superposed nodule). This was appended to the $(8m+1)$ element array Ω defined above. Henceforth we use the same symbol Ω to represent the new $(8m+2)$ element array, the last element of which is the JND-index. For a specific region k the channel decomposition results in the quantity Ω_{nk} , where the second subscript k is the region or “case” index.

To further simplify the model, and since our signals had circular symmetry, we summed over all the directional channels. The resulting radial frequency channels Ψ_n ($n' = 1, 2, \dots, m+2$) are defined by

$$\begin{aligned} \Psi_{n',k} &= \sum_{l=1}^8 \Omega_{8*(n'-1)+l,k} \quad (n' = 1, 2, \dots, m) \\ \Psi_{m+1,k} &= \Omega_{8*m+1,k} \\ \Psi_{m+2,k} &= \Omega_{8*m+2,k} \end{aligned} \quad (7)$$

where it is assumed that the 8 directional channels ($l = 1, 2, \dots, 8$) corresponding to a radial channel n' ($n' = 1, 2, \dots, m$) are sequentially ordered in $\Omega_{8*(n'-1)+l,k}$. The last two channels represent the lowest frequency channel and the JND-index, respectively. A logistic regression analysis of the data was conducted to find the optimal linear combination of the $m+2$ channels that best predicted the truth status of the region. Logistic regression (30,31) is a mathematical

technique for determining the linear combination of coefficients that best predicts (in the maximum likelihood sense) the probability p_k that region k has truth status 0 according to the model (the α and β 's are constants determined by the regression):

$$\text{logit}(p_k) = \log\left(\frac{p_k}{1-p_k}\right) = \alpha + \sum_{n=1}^{m+2} \beta_n \Psi_n \quad (8)$$

Typically we used 2000 regions half of which were normal and half were abnormal. A stepwise regression method implemented in SAS (SAS Institute Inc., Cary, NC, version 8.02) was employed for variable selection that allowed us to determine the coefficients β_n of the linear combination. The classification accuracy of the optimal logistic model was assessed by the trapezoidal area under the ROC curve (AUC) which is provided by the regression software and which was converted to the *detectability index* (d) using the transformation (13) which is analogous to Eqn. 5,

$$d = 2 \operatorname{erfinv}\{2(\text{AUC}) - 1\}. \quad (9)$$

Validation

Since interest is in predicting human observer detection performance, ideally the channelized VDM predictions should be checked with human observer detection studies. Fortunately extensive human observer detection studies have been conducted (14,32,33) for the simulated backgrounds and clinical background regions similar to those used in this work. It has been shown (14,16,33), using extensive human observer two alternative forced choice (2AFC) studies, that signal detection theory (SDT) models can predict the dependence of the detectability on target and background parameters of the type considered in this work. The results are usually presented in a contrast-detail (CD) plot, where the minimum contrast for visualization (visualization is defined, for example, by a detectability index $d = 1$) is plotted (y-axis) against the diameter of the nodule (x-axis). Depending on the background and nodule characteristics actual CD plots can have positive, negative or even zero slopes, and these verified dependences were used as the gold standard to test the predictions of the channelized VDM method.

RESULTS

Table 1 summarizes the results of the SDT method and the channelized method comparisons. There are 12 cells in the body of the table corresponding to combinations of nodule types (designer nodules with $v = 0$ and $v = 1.5$ and Gaussian nodules) and background types (uncorrelated noise, filtered noise with $\beta = 1$ and $\beta = 3$) and real mammographic backgrounds. Each cell in the body of the table (last three columns) has two entries. The first entry is the sign of the expected slope of the detectability vs. nodule size plot based on SDT, i.e., the gold standard. The second entry is the corresponding channelized VDM result. The slopes are categorized as positive (+) or negative (−). It is seen from Table 1 that the channelized VDM predictions are in excellent qualitative agreement with the SDT predictions in every case that was studied. The corresponding conventional VDM analysis yielded an initially positive slope in every case.

DISCUSSION

The data in Table 1 show that the channelized VDM method qualitatively agrees with the SDT predictions. In other words when SDT predicts that the detectability of the target should increase/decrease as a function of an externally applied change (target size, shape, edge characteristics or background) the corresponding detectability predicted by the channelized

VDM method (i.e., the d variable in Eqn. 9) also increased/decreased. In other words there is evidence that the two measurements (SDT and the channelized VDM) are monotonically related. The monotonic relationship may give confidence to the user of the channelized VDM method. One is generally only interested in whether target detectability increases or decreases when a design parameter (e.g., CRT contrast) is varied as this allows one to find the optimal value of the design parameter. As long as monotonicity is true, absolute detectability values are unnecessary for optimization studies. Of course, from a basic science view-point a quantitative validation is needed which is outside the scope of this work.

The two methods (conventional and channelized) have some similarities and some differences. The conventional VDM method requires the input of a pair of images, one with a superposed target and the same image without the superposed target (except for the superposed target corresponding pixels in the pair are identical). The predicted detectability (JND-index) is calculated for the image pair and subsequently averaged over a set of similarly constructed image pairs in order to get a better measurement in the statistical sense. On the other hand, the channelized VDM method requires two sets of images and all of the images in the sets are required to be different (i.e., from different patients). The first set must have no targets (these are the “normal” images) and each image of the second set must have a target (these are the “abnormal” images). The numbers of normal and abnormal images could be different. Both methods either have access to (by image pair subtraction in conventional VDM usage) or require knowledge of the exact shape and location of the target in the absence of any noise obfuscation (in channelized VDM). In the channelized VDM method this knowledge is needed to construct the template and to calculate the cross correlations at the correct locations on the images (Eqn. 6). These requirements restrict both methods to simulated images. For example an abnormal image is simulated by superposing a simulated target on a normal image at a known location. Since all locations on a clinical image are not equally likely to harbor a lesion, a radiologist should be consulted to guide the locations at which the simulated lesions are superposed, and to assess the overall lesion simulation process. One advantage of using simulated images is the ease with which abnormal images can be generated with known truth. It is very difficult to obtain sizeable numbers of actual proven abnormal images for ROC studies.

In the channelized VDM method one cannot predict detectability of a lesion on any individual image. One can only predict the ability of the observer to discriminate between the normal and abnormal image sets, which is also the quantity measured in an ROC or a 2AFC study. Whether this is an advantage or a disadvantage as compared to the conventional VDM method, which can in principle predict the detectability of a lesion on a single image, is left to the judgment of the reader of this journal. In actual applications the d -variable predicted by the channelized VDM method (Eqn. 9) should be used to optimize the display (one seeks to maximize d). This assumes that a preliminary calibration has been performed to determine the regression constants (α , β) in Eqn. 8. Following this one calculates the left hand side (lhs) of Eqn. 8 for $\Psi_{n,k}$ measured on a set of normal and simulated abnormal images (all images are different) and computes the trapezoidal area AUC from the lhs-values for the normal and abnormal sets, and converts AUC to d using Eqn. 9. Other methods of combining the VDM channels, e.g., Hotelling observer (34) are possible. A Hotelling observer based approach has recently been presented (35). In our opinion these methods are not fundamentally different from the logistic regression approach taken in this work since both involve finding the optimal linear combination of channels that best classifies the truth status of the regions.

The channelized VDM method is presented without any claims of superiority over the existing conventional VDM method. It is presented as an alternate method (to ROC or 2AFC measurements) to display optimization in the belief that investigators may have more confidence in a particular image quality optimization strategy (e.g., different phosphor types)

if both methods make similar predictions and the results are monotonic. It should be noted that the Hotelling observer channelized VDM implementation described in Ref. 35 is claimed to be superior to the conventional VDM method. An advantage of any VDM-based approach is that complex effects such as visual masking are automatically included in the optimization. SDT model-based predictions that do not use a similar model of the human visual system are expected to be relatively insensitive to masking effects that are known to influence human observer performance.

Among possible limitations of the study, one could question the utility/validity of using “designer” nodules. In mammography symmetric and round nodules are typical of benign cysts. Malignant masses are more likely to have irregular, spiculated margins which are more difficult to simulate. Gaussian shaped “designer” nodules were used as these are easier to simulate, and the behavior of detectability of such nodules with respect to target size and edge characteristics has been extensively studied and validated and theoretical calculations are possible. The purpose of the study was to investigate the correspondence between channelized VDM predictions and independently calculated (SDT) and experimentally validated (ROC/2AFC) detectability predictions. This aim would be more difficult to meet with clinically more realistic nodules. We are not aware of any channelized VDM study that includes the characteristics of real malignant masses. For example, the work reported in Ref. 35 used the average of 40 real masses, but the resulting mass resembled a Gaussian.

This study is restricted to the measurement and prediction of detection performance in displays. Other usages of the VDM, e.g., to determine how much image compression is tolerable before its effect becomes noticeable, do not require the presence of a lesion in one image and its absence in the other. In such studies the task is to determine if the observer can pick the compressed image (another task is considered below). A single image is used to form the paired images. One image of the pair is compressed, the other is uncompressed (more pairs are used for statistical accuracy). The presence (or absence) of a lesion in the image is irrelevant to such studies. Such studies (with identical images except for the compressed/uncompressed aspect) cannot tell the investigator which image (compressed or uncompressed) is superior for detection. For example if both images contain the lesion than one cannot ask the question: “which image contains the lesion” and get a meaningful response. In other words, one cannot measure *detection* performance with such studies. If one asks the question: “which image is superior for detection of the lesion”, then one gets a *subjective* response, with no known way to control for the lack of objectivity. For example, an observer who prefers compressed images would always select the compressed images, but the *detection* performance of the observer could actually be worse on these images, and as this quantity is not measured the investigator would not know if this is true or not. To measure objective detection task performance, in the sense of ROC or 2AFC studies, it would appear that one must use images with and without lesions in the spirit of either the conventional or the channelized VDM approaches.

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Fig 1.

This figure shows the different background regions studied in this work. Shown are: (a) a nodule-free mammographic region, (b) an uncorrelated Gaussian noise region, and three simulated power law noise regions with different degrees of spatial correlation described by the β parameter (see text) (c) $\beta = 1$, (d) $\beta = 2$ and (e) $\beta = 3$. Note the similarity of the mammogram-region (a) and the simulated region (e). The same seed was used to generate all simulated images in this example.

Table 1

This table summarizes the predictions of the channelized VDM and the signal detection theory (SDT) based methods. Each cell in the body of the table (last three columns) has two entries. The first entry is the expected slope of the detectability vs. nodule size plot, based on the SDT calculations. The second entry is the corresponding channelized VDM result. The slopes are categorized as positive (+) or negative (−). It is seen that the SDT predictions and the channelized VDM predictions are in agreement. The corresponding conventional VDM analysis yielded an initially positive slope in every case.

Background Types			Nodule Types		
			Designer Nodules		Gaussian Nodules
			v = 0	v = 1.5	
Simulated	uncorrelated Gaussian noise		+ / +	+ / +	+ / +
	power-law noise	$\beta = 1$	+ / +	+ / +	+ / +
		$\beta = 3$	+ / +	- / -	- / -
Real mammograms			+ / +	- / -	- / -