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Optimal uniformity index selection and acquisition counts for daily gamma camera quality control

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Short Title: Optimal uniformity indexes for gamma camera QC

Abstract

Introduction

The purpose of this study was to investigate the optimised use of common uniformity indexes (NEMA indexes (Differential and Integral), Cox-Diffey and the Coefficient of Variation).

Method

The indexes were calculated for induced (localised 2D-Gaussian and gradient) artefacts added to three image sets (5, 10 and 15 million counts) each containing 25 extrinsic images, using Matlab. The intensity of the induced artefacts was varied between a 1-10% maximum drop in pixel counts. The induced artefacts simulated photomultiplier tube (10cm), smaller focused artefacts (2.5cm) and gradients artefacts.

Results

For 5m count acquisitions, the Cox-Diffey, Coefficient of Variation and NEMA Integral indexes detected the 6% 2D-Gaussian artefacts (10cm-FWHM) while the NEMA Differential index performed relatively poorly. NEMA Differential and Integral indexes performed equally well at detecting smaller 2D-

Gaussian (2.5cm FWHM) artefacts. The 10% artefact was the minimum artefact detected by both indexes for 5m count acquisitions. The Cox-Diffey and Coefficient of Variation indexes did not detect any artefacts for 5m acquired counts. The Coefficient of Variation index performed best at detecting gradient artefacts at 5m acquired counts.

Conclusions

This work provides evidence that daily QC can be acquired with as few as five million counts while maintaining the same ability to detect both chronic and acute non uniformities compared to higher count acquisitions. A combination of the NEMA Integral and the Coefficient of Variation indexes gives the optimal selection of uniformity indexes providing the ability to detect a range of artefacts forms and intensities.

Keywords

Gamma camera, Uniformity, Daily Quality control, Cox-Diffey correction, NEMA

Introduction

Flood-field uniformity is one of the fundamental physical properties characterising gamma camera field of view (FOV) performance and it should be checked daily before clinical acquisitions [1]. Daily uniformity checks detect acute non-uniformities which could affect clinical acquisitions. Higher count acquisitions are required to detect changes over time. A method whereby both acute and chronic (i.e. long term trends) changes could be detected using low count daily floods would be preferable. It is common for weekly or monthly acquisitions (intrinsic or extrinsic) to be acquired with a greater number of counts (30 million (m)) [2] than used in daily quality control (QC) tests (at least 10m) [3]. There is a need for an evidence based daily QC program which minimises the acquisition times for both practical and economic reasons.

Camera uniformity must be evaluated at a count density where quantitative uniformity indices are most sensitive to detecting non-uniformities. At low count densities, an apparent non-uniformity may be due

to the inherent large statistical noise [4]. In the context of the pixel value distribution of an acquired QC image, Poissonian statistics dictate that the mean and variance of the pixel values are equivalent [4]. A pixel value distribution initially has a Poissonian form but tends towards being Gaussian in nature at higher counts.

An ideal uniformity index would require fewer acquisition counts while still maintaining artefact detection sensitivity. The performance of uniformity indexes is dependent on the artefact size, intensity and form (localised or global) although this to our knowledge has not been extensively investigated in the literature. The aim of this study is to evaluate the performance of four common indexes for a variety of common artefact types and intensities for varying acquired counts (5, 10 and 15m). The minimum number of required counts while maintaining the ability to detect changes in system uniformity performance and selection of uniformity indexes for optimal daily QC acquisitions is to be investigated.

Methods

Background

The National Electrical Manufacturers' Association (NEMA) standard [2] is widely used for quantitative analysis of uniformity. It has become the standard method used by camera manufacturers to specify camera performance. NEMA requires that the acquired images are rebinned (before processing with at least 10,000 counts collected in the center pixel of the image) into matrixes having pixel sizes of 6.4+/-30% mm. The NEMA standard defines two methods of quantitative analysis: integral and differential uniformity. NEMA defines the integral uniformity (IU) as

$$IU = \left(\frac{N_{\max} - N_{\min}}{N_{\max} + N_{\min}} \right) \times 100\% \quad \text{Eq1}$$

where Nmax and Nmin are the maximum and minimum pixel counts in the region of interest (ROI).

A disadvantage of the NEMA IU is that it only uses two pixel values in the FOV to characterise uniformity. When the integral uniformity index is

analysed for all contiguous vertical or horizontal 5-pixel sets throughout the image, it is defined as the differential uniformity (DU). The worst DU found in each direction in the FOV is reported. The NEMA standard requires smoothing (9-point weighted kernel) of the acquired image and edge stripping. The standard defines a central FOV (CFOV) and a useful FOV (UFOV). The UFOV is defined as the area of the detector used for imaging defined by the manufacturer. The UFOV does not include 5% of edge pixels that are required to be stripped from the FOV. The CFOV is the UFOV but with all the linear dimensions scaled by a factor of 75%.

The coefficient of variation (CoV) of pixel values has been recommended as a uniformity index by the Institute for Physics and Engineering in Medicine (IPEM) [3]. The next revision of IPEM report 86 [5] is likely to recommend use of the Cox and Diffey (CD) index [6] as another potential index for gamma camera uniformity. It is applied to the unsmoothed (but rebinned to 64 by 64) image matrix. This method subtracts the component of pixel value variance attributable to Poisson variance from the total pixel value variance in order to obtain a noise-free index of non-uniformity. This method is based on the assumption that the total variance of the pixel elements in a QC image can

be expressed as the sum of the variance associated with counting statistics (poisson variance which is equal to the mean count) and the variance associated with underlying non-uniformity of the gamma-camera (systematic errors).

The index can be defined as:

$$CD = \frac{\sqrt{(P \text{ var} - P \text{ mean})}}{P \text{ mean}} \text{ Eq 2}$$

where CD is the CD index, Pvar is the variance of the pixel values in the array and Pmean is the mean pixel value in the array. This index is the same as the coefficient of variation (standard deviation / mean) but with the Poisson component (Pmean) of the total pixel value variance subtracted in the numerator, i.e., the random noise is removed leaving the 'structural' component. It has also been referred to as the corrected CoV [4]. This method also requires the stripping of edge pixels like the NEMA standard. Unfortunately the original publication [6] does not provide optimal acquisition parameters or full details on the required edge stripping methodology. Both the CoV and CD indexes are global indexes as they use all the pixel values in the FOV. This is in contrast to the NEMA indexes.

In this communication methodologies were developed to compare the performance of the NEMA (IU and DU), CoV and the CD indexes for a variety of common artefact types and for various acquired counts (5, 10 and 15m). The common artefact types were induced through software manipulation of routinely acquired QC images.

Index performance for varying acquired counts and 2D Gaussian artefact dimensions

In order to compare the performance of indexes (IU, DU, CoV and CD) at detecting typical gamma camera artefacts, code was developed in Matlab (R2012a version 7.14, MathWorks, Natick, Massachusetts, USA) to calculate all the indexes simultaneously for batches of 25 QC images.

Three sets of 25 images (256 by 256 matrix 5, 10 and 15m counts) were acquired on the same head of a GE Infinia system (GE Infinia Hawkeye; GE Healthcare, Little Chalfont, United Kingdom) (59 central circular PMTs centred in FOV - 7.6cm diameter) with a Co57 flood source (C-Thru Series - 370MBq). The flood source had aged sufficiently for any impurities which could have affected uniformity acquisitions to have decayed. The 5 and 10m

images were all acquired within one month. The 15m images were produced by summing the 5 and 10m images. There was no reported change in daily uniformity performance (from inspection of manufacturer defined NEMA values) for the system over this time period showing good stability. Furthermore, this system came first in a recent national UK SPECT uniformity audit [7] proving a record for good uniformity performance.

Software artefacts were added to the QC image sets through multiplication with an artefact mask (256 by 256 matrix). The artefact mask reduces the counts in each image by the magnitude of a normalised 2D normal (Gaussian) distribution centred on the artefact mask. The intensity of the applied artefact will be referred to by the percentage decrease in counts experienced by the central pixel in each QC image (the pixel having the maximum reduction in counts). The normalisation step used in the generation of the artefact mask allows for the production of a defined percentage decrease in counts in the centre of each image array. The full width half maximum (FWHM) of the applied artefact was controlled by the user. The 2D normal artefact type will be referred to as a normal artefact throughout this manuscript.

All images were rebinned down to 64 by 64 (8.836 mm pixels) in Matlab (via summing to achieve a pixel size closest to the NEMA specified range) before calculating the indexes. Non-integer rebinning was avoided as this would invalidate the pixel noise component assumptions needed for CD index. The total array counts after rebinning were the same as before rebinning. The NEMA uniformity results were calculated for the CFOV (1536 pixels) of the images. A method based on the NEMA protocol was followed. The CD and CoV indexes were also calculated for the same array as defined by the CFOV region.

The mean indexes were calculated for all three image sets (5, 10 and 15m) for varying artefact intensities (0, 1, 2, 3, 4, 6, 8 and 10% artefact decrease in counts) and artefact diameters (2.5 and 10 cm FWHM). The 10cm FWHM artefact simulated the dimensions of a damaged PMT artefact and the 2.5cm FWHM artefact simulated generic smaller artefacts. These small artefacts could represent crystal yellowing, PMT decoupling, collimator damage or an attenuation artefact, etc.

Index performance for gradient artefacts

Horizontal (long-axis) gradient artefacts were also added to the 5, 10 and 15m image sets in order to determine index performance at detecting this form of artefact. These types of artefacts can result from incorrectly acquired correction maps, electronic faults or the use of a warped fillable Tc^{99m} flood source used to acquire daily QC images or correction maps. This type of artefact has been observed at our centre. Percentage gradient drops in counts (1, 3, 5, 7 and 10 %) were applied between the first and last pixel column in the original 256 matrixes before rebinning to 64 by 64 matrix. The NEMA indexes, CoV and the CD index were calculated for the three image sets.

Results

Index performance for varying acquired counts and 2D Gaussian artefact dimensions

Figure 1(a) shows an example 5m QC image with no induced artefact produced with the described methodology. Examples of the 10 and 15m images with induced normal artefacts are shown in Figure 1(b) and (c). The averaged uniformity index values for all image sets without any applied artefact are presented in table 1. The uniformity indexes were found to have a normal distribution as reported elsewhere [3]. The DU, IU and CoV indexes decrease in magnitude with increasing counts whereas the CD is approximately independent of counts. There is a small variability in the CD index values due to the fact that the correction has inherent errors associated with it [4] but the standard deviation is seen to decrease with increasing counts.

The mean indexes evaluated for all three image sets, for different artefact intensities (0%, 1%, 2%, 3%, 4%, 6%, 8% and 10% decrease in counts) and artefact diameters (2.5 and 10 cm FWHM), are shown in Figure 2. All mean

index responses are normalised to the mean baseline index result (no artefact) to allow for an easy comparison between indexes.

An artefact is defined as detected if the two standard deviation error bar range (for a given artefact intensity and acquired counts) does not intercept the mean baseline normalised index value of 1. This standard deviation was calculated by incorporating the baseline and index response standard deviation in quadrature for each artefact intensity. This accounted for the uncertainty in the baseline value. Table 2 shows the relationship between artefact intensity and detectability for varying acquired counts from Figure 2. Figure 2 shows that although the CD index has the greatest observed relative response, the CoV has the smallest variability.

Table 2 shows that the DU and IU indexes perform equally well at detecting 2.5cm FWHM normal artefacts for the 5m image sets. A 10% artefact is detected by both the DU and IU indexes for the 5m image sets while the CoV and CD indexes do not detect any artefact. For the 10m image set, the IU detects the 8% artefact, the DU detects the 10% artefact and the CoV and

CD indexes do not detect any artefact. The same responses are observed for the 15m image set but with the DU index detecting a 8% artefact.

Table 2 shows that for a 10cm FWHM normal artefact applied to 5m count acquisitions the CD, CoV and IU indexes can detect 6% artefacts. The DU performs relatively poorly at detecting this artefact. For the 10m image set, the CoV and Cox detect the 3% artefact while the IU and DU indexes detect the 4% and 8% artefacts respectively. This trend is also observed for the 15m count image set.

Index performance for gradient artefacts

Figure 1(d) shows an example 15m uniformity image with a 10% gradient. The mean indexes evaluated (for all three image sets) for different gradient artefact intensities (1, 3, 5, 7 and 10 %) are shown in Figure 3. Table 2 presents the relationship between gradient artefact intensity and detectability with varying acquired counts for the indexes shown in Figure 3.

Table 2 indicates that the CoV index performs best at detecting gradient artefacts for the 5m image set. It detects the 7% artefact while the IU and CD

indexes detect the 10% artefact. The CoV and CD indexes detect the 7% artefact for the 10m image set while the IU only detects the 10% artefact. For the 15m image set, the CoV and CD indexes have the same detectability (as for 10m counts) while the CoV detects the 5% artefact. The DU index does not detect any gradient artefacts for all image sets across all gradient intensities.

Discussion

The results show variability across all the tested indexes for detecting artefacts of different dimensions and intensities. Certain indexes clearly perform better at detecting certain artefact types.

It was found that the IU, CoV and CD indexes are most responsive to detecting PMT like normal artefacts (FWHM 10cm) for 5m acquired counts.

The DU index understandably performs relatively poorly at detecting this artefact due to the non-localised nature of the artefact. The CoV and CD index perform better than the IU for the 15m count acquisitions.

It was also found that the CD and CoV index were not responsive to smaller artefacts (FWHM 2.5cm). This is not a surprising result as these indexes use all the available pixels when calculating the index and hence are expected to be less sensitive at detecting smaller artefacts. The DU and IU indexes performed equally well at detecting these artefacts for 5m acquired counts.

The IU performed better at 10m counts but not 15m. It is interesting that the IU detectability varies with artefact size and type. Intuitively the IU should only depend on the maximum and minimum counts in the image. It would

then be expected that the IU would be the same for the 2.5cm and 10cm normal artefacts but this was found to be not the case. It is suspected that this difference may be due to the relative size difference between the induced artefacts and the size of the NEMA filter kernel (3 by 3 weighted pixel kernel for a 64 by 64 matrix as per the NEMA protocol). The kernel completely consumes the 2.5cm normal artefact. The kernel may have the effect of reducing the detectability of smaller artefacts. This suspicion is supported by the constant IU results for the global gradient artefact on all image sets.

This result disagrees with previous work by Hughes et al [8] which only compared indexes for a software induced artefact of a fixed size (5 by 5 pixels with corner pixels removed). The twelve outer artefact pixels had their pixel count decreased by one percentage more than the percentage drop applied to the central nine pixels. This attempted to reduce the pixel value gradient between the applied artefact and image pixels, although this equated to an abrupt vertical and horizontal artefact diameter of 3.2 cm ('step' like artefact). This assumes the suggested pixel size of NEMA of 6.4 mm. Their work found that the DU and an index measuring the spread of DU values performed best at detecting their applied artefact with abrupt edges. They also concluded that IU, DU, CoV and CD indexes appear not to be the

most sensitive uniformity indexes compared to the previously mentioned DU spread index.

The artefacts used in our work (i.e. Gaussian profile) did not have such an abrupt edge as those used by Hughes et al [8] and are, we believe, more clinically realistic. Details on gamma camera image formation can be found elsewhere [9]. The use of such abrupt artefacts in their work may have biased their results and make the IU, CoV and CD indexes appear to be less sensitive at detecting non-uniformities. We believe this may explain the differences between their results and our 2.5cm FWHM normal artefact results. The Hughes et al paper [8] is commonly cited to justify the merits of DU and the relative poor performance of IU, CoV and CD uniformity indexes [3-5].

Unfortunately Hughes et al [8] did not investigate artefacts with the dimensions of typical PMTs to allow a direct comparison with our PMT artefact results (10cm FWHM).

The CoV index was found to be most responsive at detecting gradient artefacts (for 5, 10 and 15 m acquired counts). The CoV outperformed the

CD index. While the CD gives a more 'accurate' value of non-uniformity than CoV, more noise is added by correcting the CoV. This may make the CD result less sensitive at detecting gradient artefacts. The DU index was found to be very poor at detecting gradient artefacts relative the other indexes. This is expected as local indexes are insensitive to global artefacts. To our knowledge, no study has compared uniformity indexes for gradient artefacts.

The use of the IU index in parallel with the CoV index appears to provide the optimal selection of uniformity indexes. This selection allows for the most sensitive means of detecting non uniformities of various forms and intensities over a range of acquired counts.

There is a technical limitation in the current methodology used for the creation of the software artefact. The artefacts were induced by scaling down pixel counts after the image has been acquired without changing the random noise. For a real artefact the pixels containing the artefact would also have their noise increased slightly as a result of the reduced counts although this should not have a noticeable effect on the results. The biggest artefact reduction in the acquired counts is 10% and the noise in the affected pixels

(worst case for the pixels at the centre of the artefact) would only be increased by less than this amount. In the worst case for the pixels at the centre of the artefact, the mean pixel value is 0.9 times the original and the variance will be 0.9 times the original hence the standard deviation will be 0.95. The percentage standard deviation will be $0.95/0.9 = 1.05$. Thus the effect of not increasing noise in the 'artefact' pixels should be negligible but acknowledged none the less. This work followed the original methodology used by Hughes et al [8]. Similar work could be repeated with attenuating material to replace the post-acquisition software induced non-uniformities.

This work provides evidence that quantitative uniformity indexes could be used with 5m acquired counts while still detecting non-uniformities that could potentially affect clinical acquisitions. Firstly this would reduce the frequency of purchasing new Co57 flood sources which cost several thousands of pounds each. New floods are generally purchased when the current QC flood takes too long to acquire the required counts due to source decay. This would not be the case with acquiring 5m counts during daily QC as the frequency of purchasing new Co57 flood sources could be reduced

(increased 'shelf life'). Acquiring 5 million counts has definite savings in terms of time and finances.

Typical dual headed gamma camera daily QC takes about 15 minutes to acquire 10m counts. Over a year the total time acquiring QC images is approximately 65 hours (assuming 5 days a week, 52 weeks). The total time acquiring QC images over a year could be approximately 33 hours for 5m count acquisitions. This QC approach could potentially save thousands of pounds in the cost of replacement flood sources over a period of several years and also free up more camera time for clinical acquisitions. A frequent high count acquisition (~30m) with a Tc99m point source could be used to detect chronic artefacts that are missed by the 5m count acquisitions as per recommendations [1-3]. An interesting methodology has also been suggested using the sum of multiple daily QC images in order to produce a high count image, allowing for a proposed increase in the sensitivity of detecting gamma camera non-uniformities [10].

In conclusion, this work provides evidence that daily QC can be acquired with as few as 5m counts. This type of evidence based QC protocol would

maintain the ability to detect both chronic and acute non uniformities that higher count QC protocols would have. A combination of the NEMA indexes (particularly IU) and the CoV index are the optimal selection of uniformity indexes for daily QC and provide the ability to detect PMT scale artefacts, artefacts smaller than PMTs and gradient artefacts.

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Conflict of interest statement

No conflicts of interest

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Table 1 Mean baseline uniformity indexes (%) with respective standard deviation in brackets for all image sets without any applied artefacts. Each image set contained 25 images.

Acquired				
Counts (million)	Average uniformity Index (%)			
	DU	IU	CoV	CD
5	2.62 (0.23)	3.91 (0.54)	2.50 (0.07)	0.93 (0.18)
10	2.18 (0.20)	3.43 (0.36)	1.92 (0.04)	1.01 (0.08)
15	1.90 (0.23)	3.12 (0.34)	1.64 (0.04)	0.95 (0.07)

DU, Differential uniformity; IU, Integral uniformity; CoV, Coefficient of variation; CD,

Cox-Diffey.

Table 2 Table of artefact intensity and detectability for varying acquired counts. ‘Not det’ denotes that the artefact was not detected over the range of percentage decrease in artefact counts and acquired counts.

	Counts (million)	DU	IU	CoV	CD
2.5cmFWHM normal artefact	5	10	10	Not det	Not det
	10	10	8	Not det	Not det
	15	8	8	Not det	Not det
10cm FWHM normal artefact	5	10	6	6	6
	10	8	4	3	3
	15	8	4	3	3
Gradient artefact	5	Not det	10	7	10
	10	Not det	10	7	7
	15	Not det	10	5	7

DU, Differential uniformity; IU, Integral uniformity; CoV, Coefficient of variation; CD,

Cox-Diffey; FWHM, Full width half maximum.

Figure 1 CFOV regions for example (64 by 64, windowed) daily QC images with varying acquired counts and software induced artefact types (a) 5m count image with no artefact (b) 10m image with a 5% normal artefact (FWHM 10cm) (c) 15m count image with a normal artefact 10% (FWHM 2.5cm) (d) 15m image with a 10% gradient artefact. The minimum pixel values are displayed as black and the maximum values are displayed as white in each image.

Figure 2 Bar plots of the mean index responses for varying 2.5cm and 10cm FWHM normal artefact intensities (0%, 1%, 2%, 3%, 4%, 6%, 8% and 10% decrease in counts) and acquired counts (5, 10 and 15m). Each image set contained 25 images. All indexes are normalised to the respective baseline index in table 1. The error bars represent two standard deviations of each image set normalised to baseline (0% artefact). This standard deviation was calculated by combining the baseline and index standard deviation in quadrature for each artefact intensity. The error bars on the 0% artefact intensity values represent the normalised two standard deviations for each original image set without induced artefacts.

Figure 3 Bar plots of the mean index responses for varying gradient artefact intensities (0%, 1%, 3%, 5%, 7% and 10% decrease in counts) and acquired counts (5, 10 and 15m). The error bars have the same meaning as in Figure 2.