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Basis weight uniformity analysis in nonwovens

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It is widely recognized that nonwoven basis weight uniformity affects various properties of nonwovens, including appearance, physical properties, or mechanical properties. However, it is one of the nonwoven characteristics that is most difficult to characterize. This paper reports on the methodology based on the well-known quadrant method that objectively quantifies uniformity of nonwoven fabrics.

Keywords: nonwovens; uniformity; nonwoven characterization; image analysis; basis weight

Introduction

Uniformity in a nonwoven fabric is one of the most frequently used terms when one discusses critical web properties that cannot be otherwise explained. Nonuniformity is often associated with large variations in nonwoven properties. Periodic variations of nonwoven basis weight at large scale are often considered as an indicator of process inconsistency – and a cause of pre-mature failure. It is widely recognized that basis weight nonuniformity of nonwoven fabrics affects both the aesthetic and physical and mechanical properties (Ericson & Baxter, 1973; Mohammadi & Banks-lee, 2002). However, very few studies are found in the literature dealing with this important topic.

One of the challenges in dealing with this topic is that we must identify a clear definition that is universally accepted, and that it also correlates well with our visual observations as well as performance characteristics that are influenced by nonuniformity. Uniformity has been used to refer to variations in fiber alignment and orientations (1), fiber size and shapes (2), and basis weight (3). While variations in fiber size and shape, and orientation are important structural characteristics that must also be identified and measured, it is the spatial variation of mass that concerns us in this paper. Spatial mass nonuniformity is often the cause of failure in nonwoven since it is directly related to the solidity and porosity of nonwovens locally and globally. Therefore, the term ‘uniformity’ in this paper refers strictly to “basis weight uniformity” unless noted otherwise. However, analytical methodology introduced here can be extended to other structural characteristics of nonwovens such as local variations in fiber orientation distribution that can also lead to a plethora of issues in downstream processing of nonwovens.

While there is unanimous agreement on the importance of nonwoven uniformity and manufacturer and nonwoven machine producers have made tremendous effect to achieve production of uniform nonwovens, there are no standards today for defining and/or measuring uniformity. The current practice is to measure basis weight nonuniformity or irregularity of a nonwoven fabric by the so-called cut-and-weight method (Ericson & Baxter, 1973). In this method, samples selected randomly from different parts of a nonwoven web are weighed. The coefficient of variance (%CV) of the weight is calculated and reported as the “index” of uniformity. The challenge with this is that the index is not size invariant – that is, measurements at a different size scale will yield a different index.

A number of groups have evaluated the utility of nondestructive optical-based method to measure basis weight variations. Veerabadran, Davis, Batra, and Bullerwell (1996) developed a similar procedure to the cut-and-weight method described above except that images were analyzed and the optical density was used instead to form an index. A similar attempt was made by Boeckerman (1992). Here also, when the nonwoven fabrics were uniformly illuminated through transmitted light, the intensity of the image collected by the camera directly related to optical density of samples and its basis weight (Pourdeyhimi & Kohel, 2002). Similarly, optical density measurements have been used for online-basis weight measurement (Lien & Liu, 2006). In almost all these cases, the uniformity index was based on CV% of the optical density.

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In comparison with cut-and-weight method, the image-based systems can provide basis weight mapping in high resolution and at different scales. They are fast and nondestructive and can be implemented online. However, one would need a better definition than simply using CV% for defining the spatial variability of a nonwoven. It is possible to have nonwovens that are quite different but have similar CV%. CV is a global measure of variability and ignores second-order effects with respect to spatial variation.

Another approach reported for measuring uniformity is based on the detection of defects and their distribution. This method uses the concept of outliers in the distribution to establish web uniformity. Positive outliers are indicative areas where fabric basis weight or density is abnormally high and negative outliers relate to areas with low fiber density, such as holes. The issue here is the method by which outliers are detected and identified. Cherkassky (1999) used the concept of homogeneity and inhomogeneity of random field irregular to determine outliers and used the volume of outliers as the measure of web nonuniformity.

Another defect based on uniformity analysis is reported by Lien and Liu (2006). This method also used coefficient of variation of the randomly selected region which carries the same inherent problems indicated before with respect to size dependence.

Lai, Lin, and some other researchers (Lai, Lin, Lu, & Yao, 2005; Zhou, Chu, & Yan, 2003) developed the Nonwoven Defect Detecting Method by employing the Gradient Conversion and Watershed Transformations that segment the nonwoven images into several regions. The regions are further evaluated for the "Region Average." This would allow the detection of the locations of defects (Lai et al., 2005).

To deal with the inherent limitations of the CV%, Pourdeyhimi and Kohel (2002) introduced the concept of quadrant analysis. They showed this approached can overcome size dependence of earlier methods and that the method could be used to measure overall uniformity of samples in a given image. However, the utility and sensitivity of the approach was not fully explored. A possible limitation of this study was the use of binary images as the input. Instead of optical density, they used % black area fraction as a measure of the local feature; the original grey scale image optical density is a better measure of local features. The process of converting an image to a binary one can yield possible errors.

In this paper, we extend the earlier work of Pourdeyhimi and Kohel (2002) to gray scale images, and introduce a new uniformity index. We use gray scale intensity instead of area fraction (% of black in the image) so as to minimize any errors due to segmentation to a binary image.

Experiments

Materials

In order to verify the correctness of the method, sample images with known uniformity are needed. For this, we have used two series of images: a set of simulated images with varying uniformity through controlling cluster structures and a set of wet-laid nonwovens with varying degrees of uniformity. The second set is the same as the one used previously by Pourdeyhimi and Kohel (2002).

Basis weight variation results in different degree of blotchiness because the mass variations yield different brightness values in the final image (Pourdeyhimi & Kohel, 2002). Thus, the first set of images consists of simulated binary images and variations of local brightness were created by introducing clustered objects. Figure 1 illustrates an image with highly clustered objects and an image where objects are randomly/uniformly distributed without presence of any clusters. In

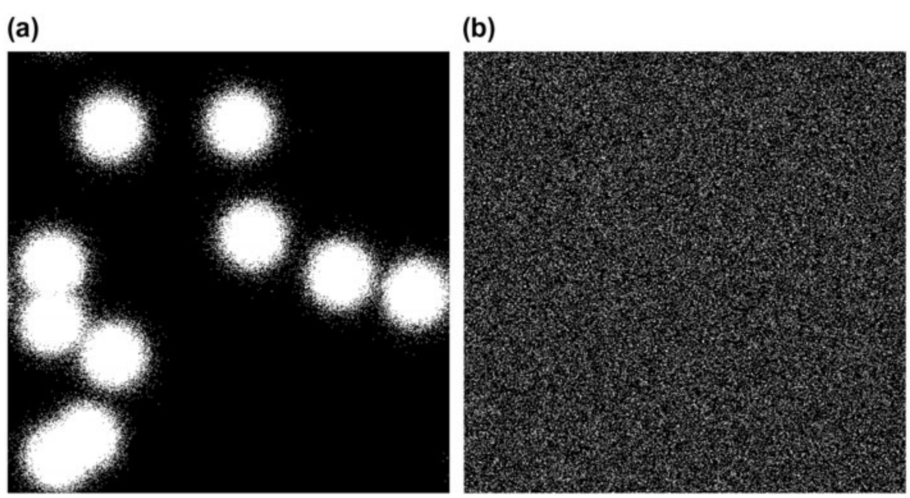

Figure 1. Images of clustered objects (a) and random objects (b).

both cases, the area fraction was kept constant at 20%. Clearly, images with clusters can model extreme nonuniformity of a nonwoven while a random object distribution can model a more or less uniform web.

To create model images with different degrees of clustering, we use dispersion or scattering of objects in the cluster to control the degree of nonuniformity created by the cluster. Each cluster consists of a pre-determined number of objects and the dispersion of clusters is determined by the radial distribution of distances between objects from the center of the cluster. In each cluster, the distance between the cluster center and the objects followed by a normal distribution, $f(x)$:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}, \tag{1}$$

where x = distance from the center; μ = average distance from the center; and σ = stand deviation.

As the standard deviation of the object-cluster center distribution increases, the cluster becomes more dispersed and the spatial uniformity of images increases. To control cluster dispersion, we use normalized standard deviation with size of clusters and defined CWF (cluster width factor).

$$\mathrm{CWF} = \frac{\sigma}{W}, \tag{2}$$

where W = width of average area that one cluster occupied, $W = \frac{\text{Image area}}{\sqrt{C_n}}$, and C_n = number of clusters.

In each cluster, the distance between the cluster center and the objects followed a normal distribution of (0, W × CWF). This concept is demonstrated in Figure 2. It shows objects-cluster center distance distributions and images of the clusters, when the distribution becomes flat and the image becomes uniform.

We expand this concept to create images of multiple clusters with varying degrees of object dispersion using the following procedures: binary images of 600 × 600 pixels are created and with a given number of clusters, C_n. We created two sub-sets of images – a random set where a center points are selected randomly (Figure 3) and a uniform set where cluster center points are uniformly distributed (Figure 4). Then members for each cluster are added until reach a pre-determined area fraction of 0.2. The distance between cluster center and members followed the normal distribution of (0, W × CWF).

As mentioned above, a second set of samples consists of four wet-laid nonwovens with visibly varying degrees of uniformity (Figure 5). Since uniformity differences are obvious in these samples, we use these as a reference set for guiding and checking the uniformity analysis method developed.

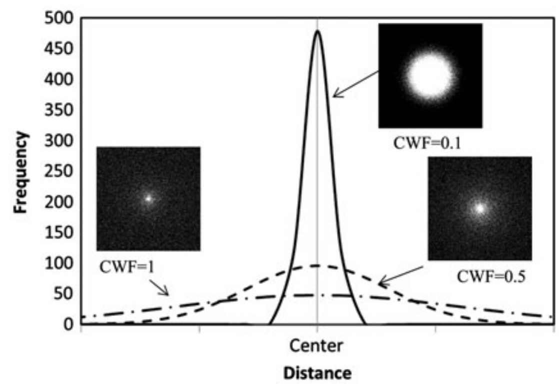

Figure 2. Center-to-object distance distribution of a cluster with different CWF.

Image acquisition

To have an image whose optical density is correlated with its basis weight, we use transmitted light. The areas with high basis weight would produce darker shade in images while the area with low basis weight would produce bright area in the images as less material to absorb/scatter light transmitting through it.

There exist two additional challenges. The first relates to the size of the specimen required for the analysis. Basis weight variation occurs at relatively large (macro) scale and, therefore, it is essential to obtain a sample large enough to be representative of the overall fabric structures. For this, we used a flatbed scanner (Epson Expression 1640XL) equipped with film scanning capability through transmitted light (Figure 6). It provided abilities to obtain high resolution data-set and relatively fast data collection speed.

The second challenge relates to possible artifacts during image acquisition. To address this issue, the images were normalized by equal probability quantization method commonly referred to as histogram equalization or histogram flattening (Pourdeyhimi, Xu, & Wehrle, 1994). This procedure removes any deviations caused by the adjustment of the illumination system. The result of histogram equalization for one image is shown in Figure 7 before and after histogram flattening. It should be noted that although the first-order statistics are normalized, second-order statistics are not affected; spatial variations remain unaltered. In Figure 8, images of wet-laid standard sample set after histogram equalization demonstrate this.

Naturally, we also have to establish the limitations of image capture parameters that may influence the results. Therefore, images with different resolution and size were examined. All images were digitized at the same settings at various resolution ranging from 100 to 1200 dpi in sizes ranging from 1.3 × 1.3 to 20 × 20 cm^2. All images were 8 bit gray scale images.

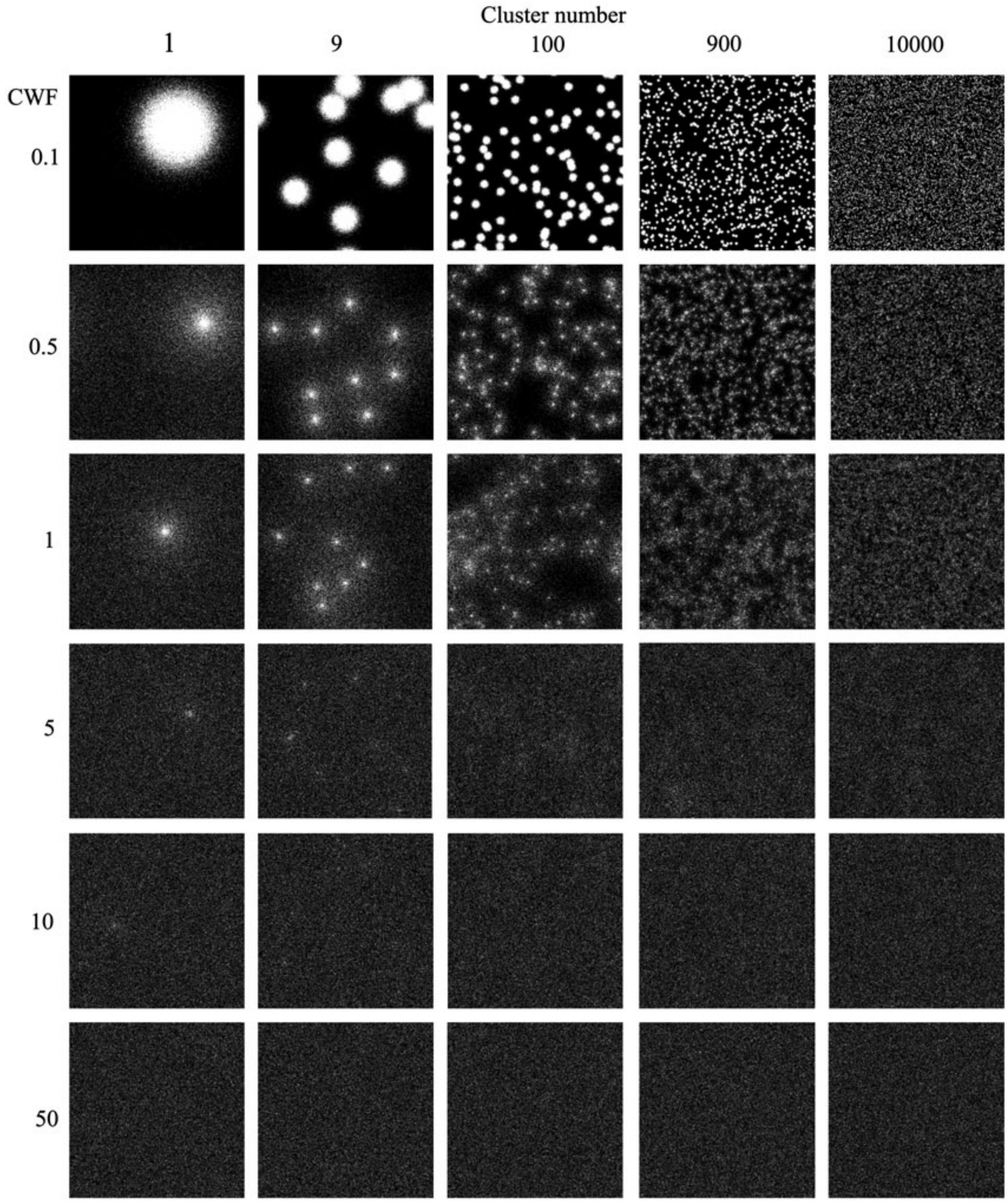

Figure 3. Simulated images. Randomly arranged clusters.

Methodology

The Quadrant method is one of the techniques used in ecology (Greig-smith, 1964) and forms the basis for our technique. The outline of the procedure is shown in Figure 9. A sample image is broken up into a number of windows, and the basis weight data $M_k(x,y)$ are collected. Gray scale of each pixel in the image is assumed to represent the basis weight of that pixel. x and y are the window positions and k is the size of windows. The number of windows is varied by $n=i^2$ for $i=2, \ldots, N$. At each i, the index of dispersion and Chi-square value are calculated via Equations (3) and (4), respectively, at the size scale of the window size used. The index of dispersion, I, has been used to test departures from the randomness and presence of patterns in spatial distributions (Perry, 1979).

$$I = \frac{\text{observed variance}}{\text{observed mean}} = \frac{s^2}{\bar{x}}. \tag{3}$$

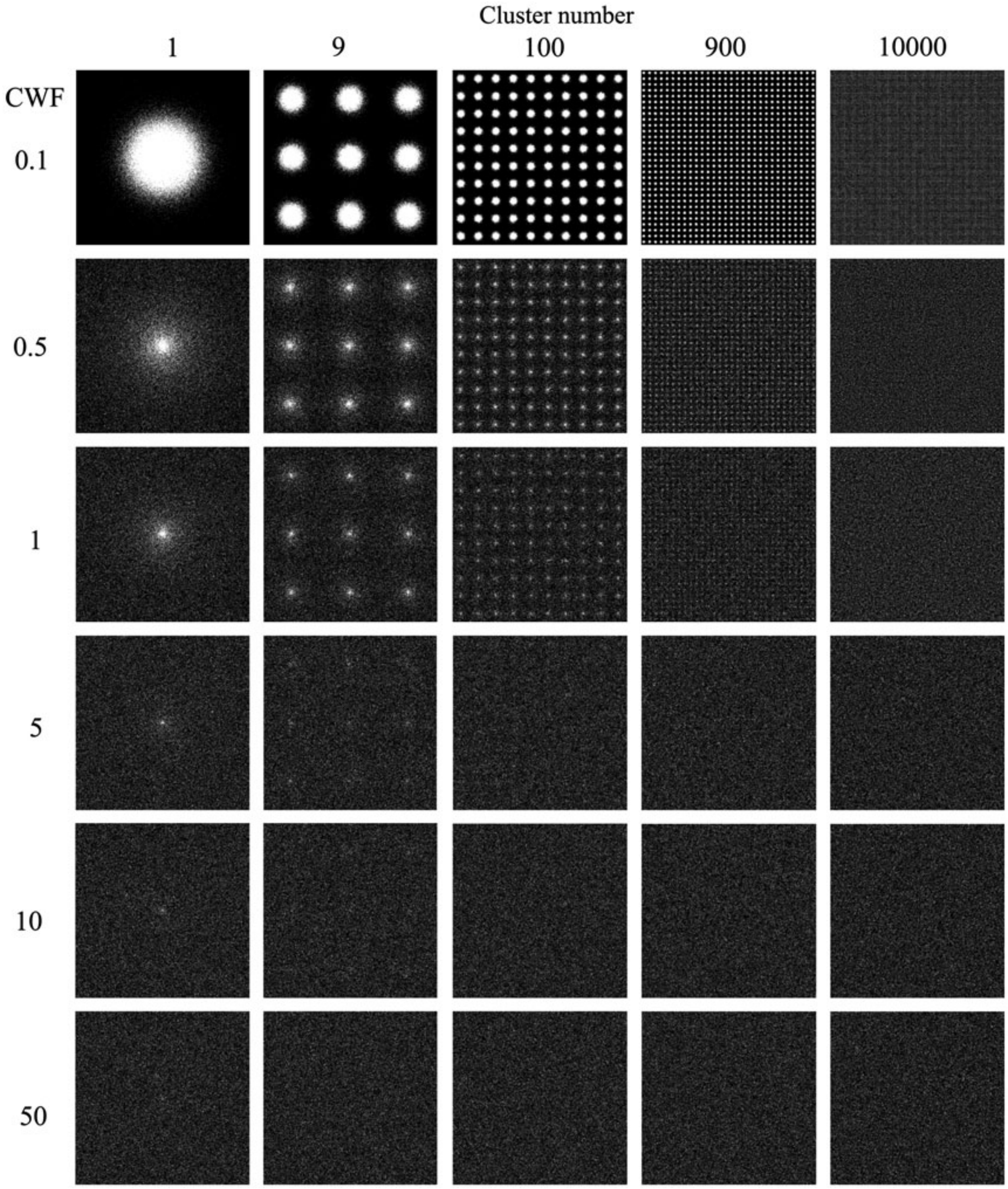

Figure 4. Simulated images. Uniformly arranged clusters.

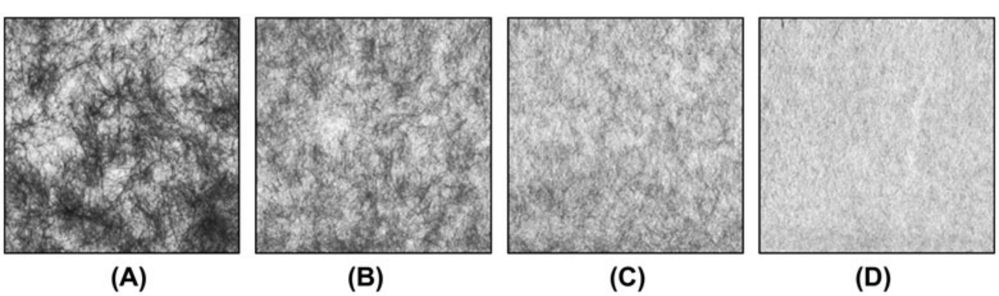

Figure 5. Images of the wet-laid reference set.

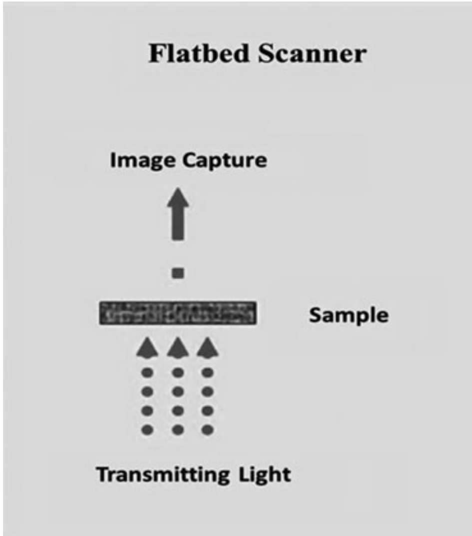

Figure 6. Schematics of the image capturing procedure.

For random spatial distribution, the index of dispersion becomes 1 as x (or density) has a Poisson distribution with $\mathrm{Var}(X) = E(X)$. Then, $I < 1$ indicates spatially uniform distribution and index of dispersion, and $I > 1$ indicate presence of clusters or patterns. Randomness can be tested by using Chi-square χ^2 statics from:

$$\chi^2 = I(n-1), \tag{4}$$

where n = number of quadrants, $\overline{X}$ = mean of gray scale, and s^2 = variance between the squares.

The graph of χ^2 values plotted versus degree of freedom $n-1$ (see Figure 10) can be used to provide a measure of uniformity. At 95% confidence interval, the image can be considered random when $\chi_{0.975} < \chi^2 < \chi_{0.025}$. $\chi_{0.975} > \chi^2$ indicate perfectly uniform dispersion. For $\chi^2 > \chi_{0.025}$, the image is considered as clustered.

We define uniformity by the rate at which the χ^2 changes with size (n). If a sample is perfectly uniform, it will have the same value regardless of the size. As it becomes more nonuniform, however, the rate of change becomes steeper. Therefore, we measure uniformity by calculating an index (UI) based on the area under the Chi-square graph:

$$\mathrm{UI} = \frac{1}{1 + \frac{A}{a_0}} \times 100 \tag{5}$$

where a_0= area below curve $\chi^2_{0.0275}$ and A= area below Chi-square of sample, $A = \int_0^{100} \chi^2 dn$.

Then, UI = 100 indicate the perfectly uniform sample, where $A = 0$. UI higher than 50% incidates that $A > a_0$, where clusering may be present in samples. UI will become 0 for samples with infinite A.

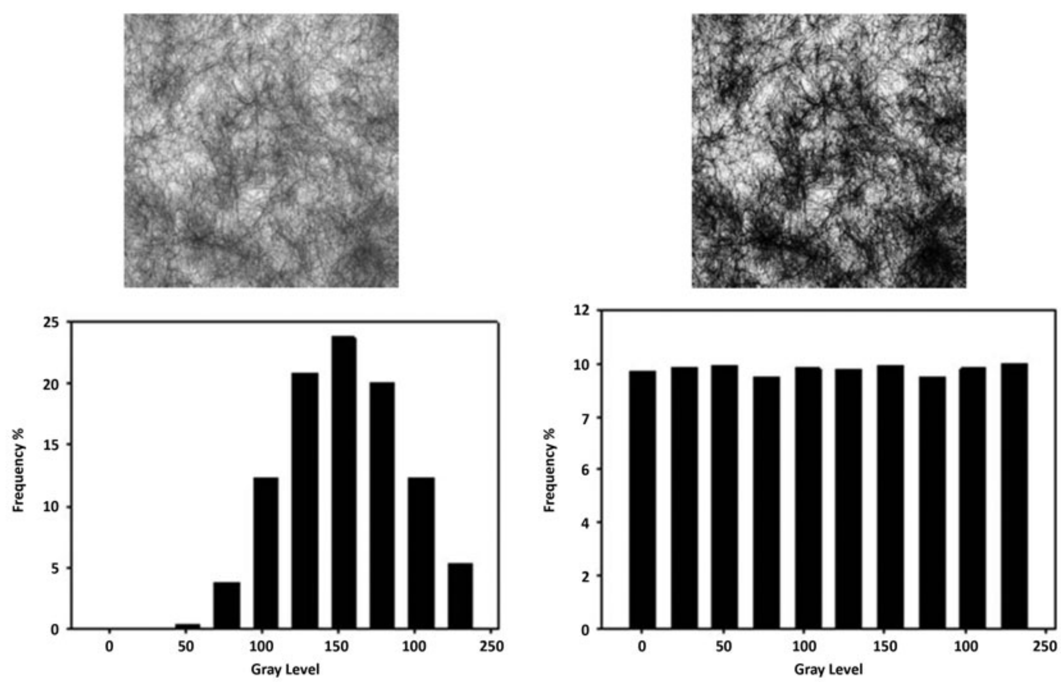

Figure 7. Original wet-laid sample (left) and after equalization (right) and their gray scale distribution.

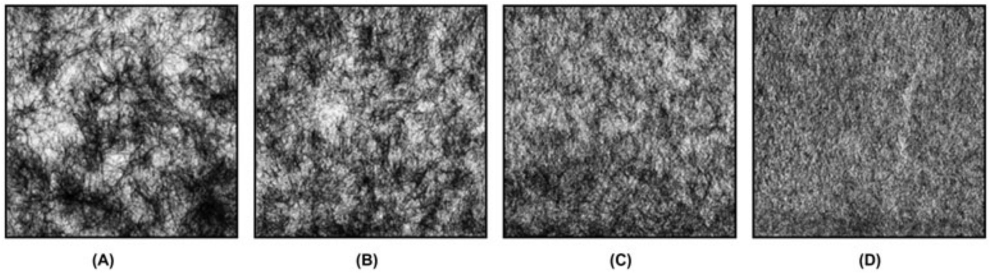

Figure 8. Images of the wet-laid reference set after histogram equalization.

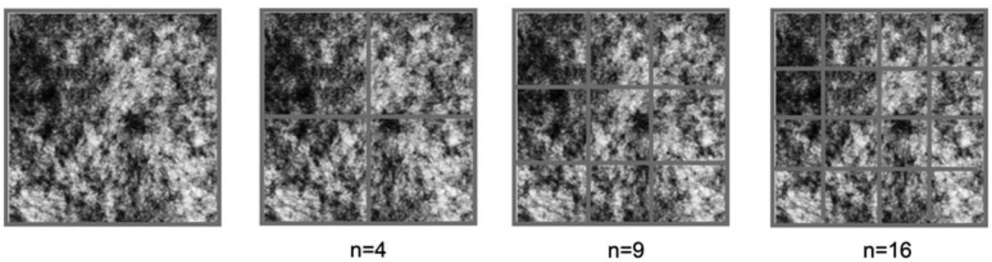

Figure 9. Procedure of uniformity analysis using quadrant method.

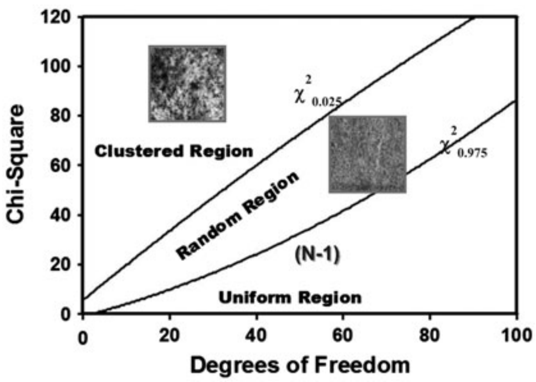

Figure 10. Chi-square vs. degrees of freedom.

Result and discussion

Uniformity analysis of simulated Images

As previously mentioned, we have altered the dispersion of objectives in clusters to create varying degrees of uniformity. First, we used the simplest case where images have only one cluster. Images of one cluster with varying CWF and center position are given in Figure 11. In the first set, cluster centers are always positioned at the center of the images, and in the second set, cluster center positions are picked randomly.

Chi-square curves of them are given in Figure 12. As expected, the results of highly clustered images (low CWF) show sharp increases in Chi-square value with increasing number of n. As CWF increases, images become more uniform, and the slope of the curve decreases. This general trend is not influenced by a position of a cluster. However, it affects local variation of the slope. When a cluster is positioned at the center, it created periodic variations. But, because we use the area under the curve, this variation does not affect the UI values. The uniformity indices of single cluster images are shown in Figure 13. It shows uniformity index increases as CWF increases and it well agrees with visual assessment. As previously mentioned, spatial uniformity increased with the dispersion of the cluster objects; high CWF images exhibit a high uniformity index. In addition, uniformity index is not affected by the cluster position. At a given CWF, UI of a cluster randomly positioned is almost identical to that of a cluster placed in the center.

Next, images having different numbers of clusters were analyzed and are presented in Figure 14. These results clearly demonstrate that an increase in CWF leads to a higher uniformity index.

Another interesting point shown in Figure 14 is the effect of the number of clusters. Cluster number does not affect uniformity index when it is less than 100. However, when there is a large number of clusters present, UI increases. This agrees well with our visual observations as well. As shown in Figures 3 and 4, when there is a large number of small clusters, images look uniform regardless of cluster dispersion.

Next, we compared UI results of images between clusters with uniform spacing and random spacing. Results shown in Figure 15 demonstrate that UI increases with uniform cluster spacing.

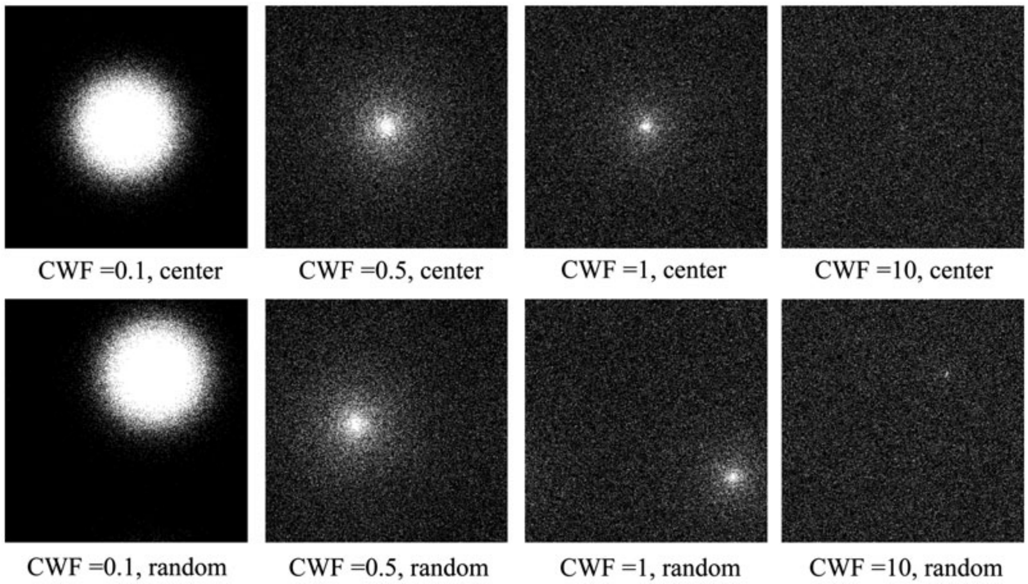

Figure 11. Images of single cluster with different center position and CWF.

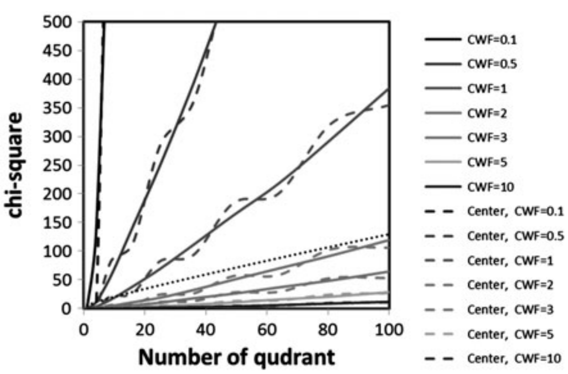

Figure 12. Chi-square curve of simulated images with one cluster.

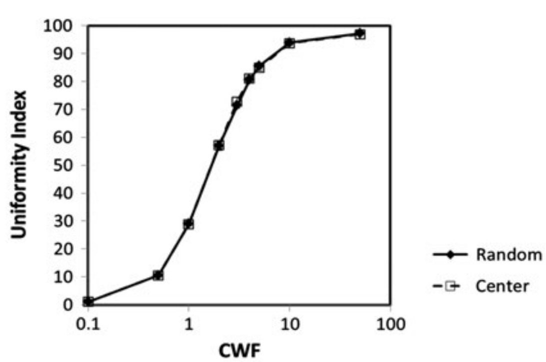

Figure 13. Uniformity index of single cluster images.

For all of our simulated images, UI values appear to correctly quantify uniformity. Our index detects nonuniformity caused by the presence of dense clusters

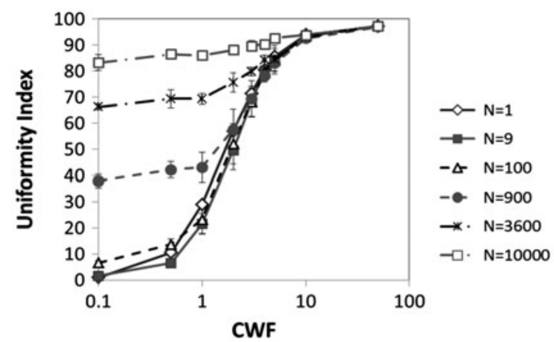

Figure 14. Uniformity index of simulated images with different CWF and cluster number: random set.

(low CWF yields low UI), and large clusters (small number of large cluster yield low UI), and the arrangement of clusters (uniform arrangement of cluster yield high UI). These results agree well with our visual observations.

Uniformity index of nonwovens and the effect of imaging parameters

The set of real nonwoven webs with distinguishable degrees of uniformity was also evaluated by using the same procedure outlined above. As shown in Figure 5 and it is obvious that sample *D* is most uniform while sample *A* is least uniform. Sample *B* and *C* appear to be in the middle. UI results of these samples, shown in Figure 16, agree well with our visual observations.

As indicated before, it is essential that we determine the influence of image acquisition conditions on the UI.

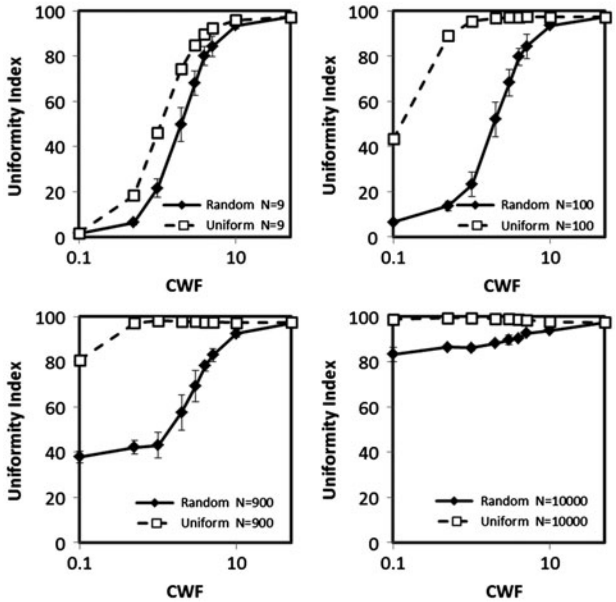

Figure 15. Uniformity index of simulated images: random vs. uniform clusters.

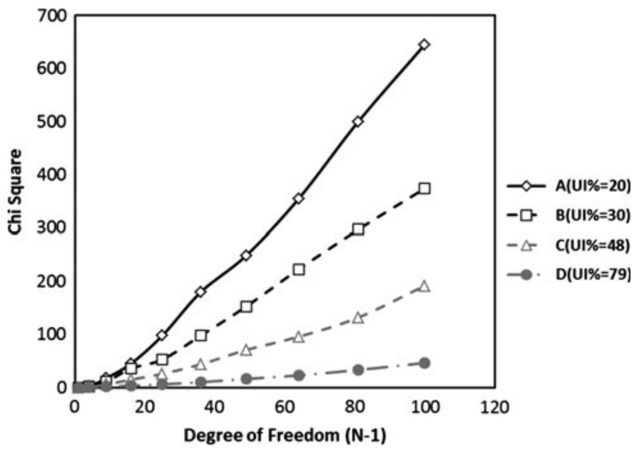

Figure 16. Chi-square curves of wet-laid reference nonwovens (sample size: 12.5 cm × 12.5cm, scan resolution = 600 dpi).

Thus, we investigated the sensitivity of UI to image resolution and image size. The uniformity index as a function of resolution (dpi) is shown in Figure 17. Sample size was kept at $15.2 \times 15.2\,\mathrm{cm}^2$. This result shows that the uniformity indices hardly changes as function of imaging resolution variation after 300 dpi. This indicates the UI is not highly sensitive to image resolutions, so UI can be used to evaluate uniformity of fabrics regardless of image resolution as long as it kept higher than 300 dpi. This indicates UI is not highly dependent on image resolution and 300 dpi is sufficient for determining uniformity.

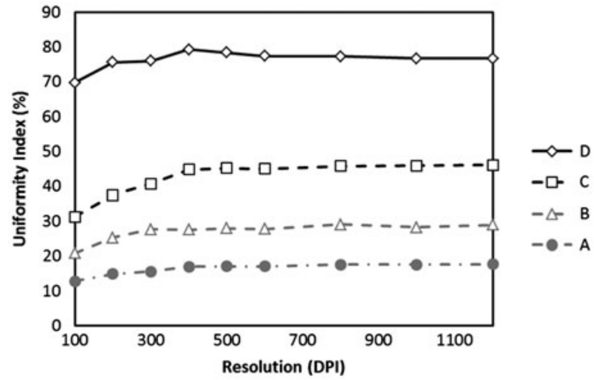

Figure 17. UI(%) of wet-laid reference nonwovens – effect of resolution.

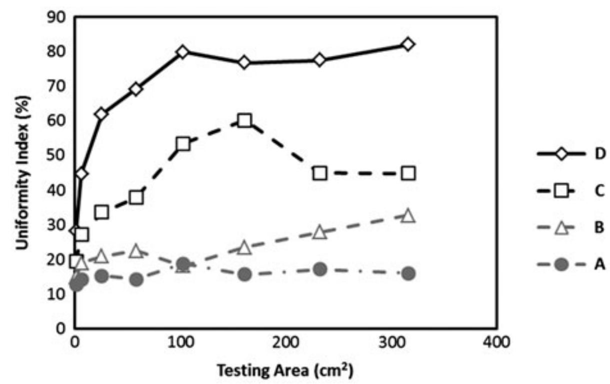

Figure 18. UI(%) of wet-laid reference nonwovens – effect of testing area.

The uniformity index as a function of sample size is shown in Figure 18. For these, image resolution was kept at 600 dpi. This result shows smaller the sample size yield the lower UI in all sample tested. As sample size increases, dependency on sample size decreases and the uniformity indices hardly changes as function of sample size variation after $15.2 \times 15.2\,\mathrm{cm}^2$. Again, this indicates sample size of $15.2 \times 15.2\,\mathrm{cm}^2$ is sufficient to evaluate uniformity of nonwovens.

Note that under almost all testing conditions, the relative ranking of UI index for these four samples remained unchanged. This implies that for a given set of conditions, the ranking will remain the same even though absolute values of UI index may be influenced by sample size and resolution. This means that we must establish and use conditions that are kept constant when comparing samples.

Conclusion

The Quadrant method was adapted for analyzing uniformity in nonwovens through image analysis. Images were acquired by using a flatbed scanner using transmitted light. The gray scale of each pixel of the image (optical density) was assumed to be a good indirect measure of basis weight at that point. Finally, we defined a uniformity index as a quantitative descriptor of nonwoven uniformity which appears to be quite robust.

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