To measure temperature, the device was placed on top of a heating element of a thermoelectric heat controller. The arrangement was enclosed in a plastic box to maintain a constant temperature across the length of the device. Again, both ends of the fibre were fixed with a tape to maintain a constant strain on the device. Temperature around the device was varied from 22 to 102°C and the corresponding spectral changes were captured using the OSA.

When the cascaded-LPG device was tested against temperature, a different behaviour emerged, with peaks ‘f’ and ‘g’ of the cascaded LPG device red-shifting with increasing temperature. Typically, peak ‘f’ of LPG1 shifts ~19.4 nm whilst peak ‘g’ of LPG2 shifts ~5 nm for a temperature rise from 22 to 100°C, as shown in Fig. 2b. The temperature cross-sensitivity that could affect the SRI measurement using LPG2, therefore, can be compensated using the information extracted from LPG1. We have evaluated the temperature sensitivity of peak ‘f’ of the index-insensitive LPG1 of the cascaded device, the value obtained is $\Delta \lambda_{f, \text{insensitive}} / \Delta T = 194$ pm/°C, which is 16 times greater than that of the index-insensitive component of the SFBG we reported earlier [5].

We also note that since peak ‘f’ of LPG1 is insensitive to SRI and it is in the 1500 nm region, by embedding the grating in a relevant material its temperature sensitivity can be reduced, paving the way for the application of such types of grating for gain-flattening applications.

**Conclusion:** We have demonstrated, for the first time to our knowledge, the capability of a cascaded LPG device fabricated in a double-cladding fibre to measure the surrounding refractive index and temperature simultaneously. The index insensitive LPG used to make up the device has temperature sensitivity that is 16 times greater than that of the Bragg peaks of the SFBG used for a similar application.

**Acknowledgements:** The authors wish to thank T. Hart of Fibrecore Limited for providing the fibre, and also acknowledge the support provided by the UK EPSRC and the Kebbi State Government of Nigeria.
the fingerprint image is acquired. The parameters for the image normalisation are then adaptively determined according to statistics such as the estimated mean and variance of each block.

Adaptive image normalisation based on block processing: For a given fingerprint image $I$ which is defined as an $N \times M$ matrix and $I(i,j)$ represents the intensity of the pixel at the $i$th row and $j$th column, Hong and Jain employed the following normalisation processing [2]:

$$G(i,j) = \begin{cases} 
\frac{\text{VAR}_d(I(i,j) - \bar{M})^2}{\text{VAR}} & I(i,j) > \bar{M} \\
\frac{\text{VAR}_d(I(i,j) - \bar{M})^2}{\nu} & \text{otherwise}
\end{cases}$$

(1)

where $\bar{M}_d$ and $\text{VAR}_d$ are the desired mean and variance values, and $\bar{M}$ and $\nu$ are the computed mean and variance of the given image.

The desired $\bar{M}_d$ and $\text{VAR}_d$ should be pre-tuned according to the characteristic of the input image. These desired values are fixed but the input fingerprint images which are obtained from sensors may have imperfections or be of poor quality owing to the non-uniformity of the ink intensity or the non-uniform contact with the sensor by users. To solve this problem, we propose a new normalisation method with the adaptive values $\bar{M}_d$ and $\text{VAR}_d$ for the local region in the given fingerprint image.

For a given fingerprint image, the proposed normalisation algorithms are composed of the following steps: (i) histogram equalisation, (ii) selection of the region of interest (ROI) and (iii) adaptive normalisation based on block processing.

(i) Histogram equalisation: Histogram equalisation defines a mapping of gray levels $p$ into gray levels $q$ such that the distribution of gray levels $q$ is uniform [4]. This mapping stretches contrast for gray levels near the histogram maxima and improves the detectability of many image features.

(ii) Selection of region of interest (ROI): Since the image has some background noise, the algorithm may process the area outside the fingerprint. This can cause an erroneous feature in the algorithm, thus the fingerprint area in the input image should be pre-selected in advance. To do this, the input image is divided into the non-overlapped $K \times L$ blocks. In this work, we have utilised a $16 \times 16$ block. Among all partitioned blocks, the blocks which have a high variance of the gray level are selected for the next steps. Let $\nu$ be the variance of the gray level for $i$th block, the block classification is performed as follows:

$$R_{ROI} = \begin{cases} 
B_{\text{Origin}} & \text{if } \nu > \nu_t \\
0 & \text{otherwise}
\end{cases}$$

(2)

where $B_{\text{ROI}}$ is the region of interest, $B_{\text{Origin}}$ is the original image data, and $0$ is a zero block in which all elements are zero values. Since the homogenous region may exist in the interior of the fingerprint image, it is necessary to filter the pre-classified image of the given input. We devise the two-step filtering procedure, i.e. removing and filling techniques.

(iii) Adaptive image normalisation based on local property: For the acquired ROI, the initial $\bar{M}_d$ and $\text{VAR}_d$ are first estimated utilising the statistics of the ROI. These play a role as the reference value in the adaptation processing.

Algorithm 1: For the estimated initial $\bar{M}_d$ and $\text{VAR}_d$ and the ROI, the normalisation procedure is performed on the ROI by block unit processing. Although the $\bar{M}_d$ and $\text{VAR}_d$ are fixed, the block-based normalisation can enhance the given ROI by considering local properties such as the mean and variance of the processing block.

Algorithm 2: For the estimated initial $\bar{M}_d$ and $\text{VAR}_d$ and the ROI, $\bar{M}_d$ and $\text{VAR}_d$ are varied to adapt for the local properties of the current block. Let $\bar{M}_d$ and $\text{VAR}_d$ be the desired parameters for normalisation of the $i$th block in the ROI, the updating equations are written as follows:

$$\bar{M}_d^t = \bar{M}_d^{t-1} - \alpha_1 \cdot (\bar{M}_d - \bar{M}_d^t)$$

(3)

$$\text{VAR}_d^t = \text{VAR}_d^{t-1} - \alpha_2 \cdot (\text{VAR}_d - \text{VAR}_d^t)$$

(4)

where $\alpha_1$ and $\alpha_2$ are the weighting factors which represent the degree of contribution of the variation term, $\bar{M}_d$ and $\text{VAR}_d$ are the computed mean and variance of the $i$th block, respectively. The second terms of the above equations are the variations which are considered the local properties of the $i$th block. As these terms contribute to the desired parameters, the desired parameters are changed according to the local properties of the current block.

Simulation results: To verify the proposed algorithm, we have used fingerprint images from the database of NIST fingerprint image groups. The NIST images derive from digitisation of the inked fingerprints, each consisting of $512 \times 480$ pixels, in the 8-bit gray scale. For processing the block unit, the size of the partitioned block is selected as $16 \times 16$ in this work.

Figs. 1 and 2 show the results when $\alpha_1 = 0.3$ and $\alpha_2 = 50$ and $\text{VAR}_d = 100$. As the results show, the conventional normalisation method could not enhance the image well since it did not consider the local properties [1, 2]. However, the proposed algorithms that utilise block-based processing enhance the original image by using the devised adaptive normalisation. The proposed algorithm 2 yields a more reliable result than algorithm 1, this being due to consideration of the local properties.

![Fig. 1 Result for NIST-f01](image1)

(a) Original image
(b) Conventional method
(c) Block-based normalisation with fixed desired parameters (algorithm 1)
(d) Block-based normalisation with adaptive parameters (algorithm 2)

![Fig. 2 Result for NIST-f10](image2)

(a) Original image
(b) Conventional method
(c) Block-based normalisation with fixed desired parameters (algorithm 1)
(d) Block-based normalisation with adaptive parameters (algorithm 2)
Area histogram for image analysis

Zhi-Gang Wang, Wei Wang and Xiao-Ming Xu

The notion of an area histogram is considered. Typically, an area histogram of an intensity image is based on the statistics of connected components created by thresholding decomposition of the gray-level function, which can contain more information than a conventional intensity histogram and can be used to analyse an image in scale space.

Introduction: The scale of objects, as well as the intensity, is an important feature of a digital image. However, so far we have no systematical method that can be used to describe the scale of all the objects in an image, although there are many multiscale approaches to analyse an image from different aspects of the image. In this Letter, we propose the notion of an area histogram from an intuitive point of view and discuss its basic properties. Moreover, examples illustrating the use of an area histogram are described.

Area histogram: First we consider an area histogram for a set of ordered elements. The notion of an area histogram can be defined as follows:

Definition 1. For a set of ordered elements, an area histogram is the function of the area of connected components [1] in the set, describing the number of connected components of every area, and its horizontal axis is area and its vertical axis is the number of connected components created by thresholding decomposition of the gray-level function, which can contain more information than a conventional intensity histogram and can be used to analyse an image in scale space.

Definition 2. For the gray-level function of an image, the area histogram is a function of the area of the connected components in all the associated level sets \( S_l, l = 0, \ldots, K - 1 \), describing the number of all the connected components in every area. This means that an area histogram of an image represents the area distribution of all connected components in the associated level sets, i.e., for an area-scaled image, an area histogram shows its scale distribution, so that it can be used to analyse an image in area-based scale space. Moreover, for an image of size \( M \times N \), if we remove the point \( \text{area} = M \times N \) in the area histogram, it has nothing to do with the illumination, therefore the area histogram can be used as the illumination-invariant representation of the image. In the following Section, we will use this illumination-invariant area histogram, still simply called an area histogram, to analyse the image.

Example of image analysis based on area histogram: The aim in the following Sections is to illustrate some possible applications of the notion of an area histogram. To this end, a pyramid of connected operators [1] and sampling of scale space are analysed using an area histogram.

Pyramid of connected operators: A pyramid of connected operators is defined in [1] as a family of connected operators \( \{ \psi \} \) depending on a positive parameter \( \lambda \) such that, for each \( \lambda \geq \mu \geq 0 \), there exists a given \( \nu \geq 0 \) such that \( \psi \psi^\lambda = \psi^\nu \), where the equals sign means that the left is strictly equal to the right on every numerical value. However, from the definition of connected operators in [1], we know that the connected operators are only selective in connected components and do not add new connected components to the processed image (i.e., connected invariant). Moreover, an area histogram is only relevant to the connected components distribution in an image, and has immunity from the illumination which is possibly changed by connected operators \( \{ \psi \} \). Provided the area histogram is identical, we have reason to believe that the images obtained from the same original one using connected operators \( \{ \psi \} \) are the same. Therefore, we can define the pyramid of connected operators again using an area histogram as follows.

Definition 3. For each \( \lambda \geq \mu \geq 0 \) if there exists only a given \( \nu \geq 0 \) such that \( \psi \psi^\lambda = \psi^\nu \), where symbol \( = \) denotes the area histogram of the left "equals" to that of the right, the family of connected operators \( \{ \psi \} \) is a pyramid of connected operators. From this definition, it is easy to establish that many connected operators, such as morphological dilation/erosion by connected structure elements, area opening/closing [1], are a pyramid of connected operators, and morphological opening/closing by connected structure elements, area open/close/close-open [3], are not a pyramid of connected operators.

Sampling of scale space: When using the connected operator to construct the image scale space, such as area opening/closing, sampling the scale domain is a problem initially. For a discrete sampling of scales, the most obvious sampling would include scales \( S_{\min} = 1, \ldots, S_{\min} - 1, S_{\min} \), where \( S_{\min} \) and \( S_{\max} \) are the minimum and the maximum area of connected components, respectively. Nevertheless, the straightforward sampling of the image scale may cause over-sampling since not every scale exists in the original image. A sampling scheme for the scale parameter based on "granulometry" is discussed in [3] (we provide a brief summary here). The normalised granulometry for the scale space \( \{ f \} \) is defined by

\[
G(s) = \frac{1}{|f|} \sum_{l=1}^{1} \left| f_{l, s}(x, y) - f_{l}(x, y) \right| 
\]