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An Introduction to Deep Learning

This technology will be used to enhance and improve identification of structural damage

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Deep learning (DL) is a subset of machine learning, the science of using computers to improve performance without problem explicit programming. Thanks to recent advances in computer architecture, data acquisition and storage systems, and software tools, DL has become the dominant focus for artificial intelligence (AI) research and development. The goal of this article is primarily to describe the DL process and briefly illustrate an example that will enable professional structural engineers to automatically label images. More detail on the example is provided in the references.

Much DL research has been concentrated on the development of computer instructions (algorithms) to classify data. Many DL algorithms have been designed to find and report patterns in data without any preprocessing of these data—this DL application is known as unsupervised learning. Other DL algorithms learn from data sets (training sets) by correlating patterns in the data with classifications provided by human experts (ground truth data)—this DL application is known as supervised learning. Supervised learning is like learning with a teacher who tells you what is the right answer and guides you; unsupervised learning is like learning without a teacher and your task is to find the patterns in the data on your own. In this article, the focus is only on supervised learning.

After training, DL algorithms become tools that are used to categorize new data sets. Many of these DL models (generally termed algorithms) can assess data faster and more accurately than expert practitioners. For example, radiologists can now use DL algorithms to conduct analyses of images used for cancer detection.[1] The algorithms are adept at identifying incipient tumors and alerting the radiologists to the need for closer examination. In another example, DL algorithms are also being developed to allow unmanned aerial vehicles (UAVs) to assist in inspection of civil infrastructure by autonomously directing themselves to a pertinent structure, then sub-areas in the structure, and then specific, probable anomalies.[2] Images created by these UAVs can then be analyzed by yet another DL algorithm to automatically identify and tag structural damage. The resulting collection of tagged images can then be used by structural engineers to determine appropriate actions.[3,4] Similar technologies can also be used to train machines capable of autonomously working in hazardous environments[5] or to manage inventory in civil infrastructure projects.[6]

The future of image recognition in civil infrastructure will be enhanced by advancements in theory and capability of computer vision systems. This will not be a substitute for the knowledge of expert structural engineers; rather, by highlighting damages in images, such DL algorithms will facilitate more rapid and targeted analysis by experts. DL solutions are currently being researched and implemented to solve civil engineering related problems. As these techniques become implemented by civil engineers around the world, DL can contribute to the surveying and improvement of infrastructure on a larger scale.

The Deep Learning Process

Overview

DL algorithms are built from artificial neural networks (termed ANN or NN). In general, an NN is comprised of interconnected nodes (called neurons) that are arranged in layers. While neurons within a particular layer are independent of each other, the neurons in a layer are linked to the neurons in preceding and following layers by functions with variable weights. The term “neuron” was assigned to nodes in NN because the multiplicity of connections between nodes can be likened to the synaptic connections between neurons in a brain. For supervised learning algorithms, the weights in the NN algorithm are determined during a training step, by an iterative process that minimizes errors between classifications made by the algorithm and classifications provided in ground truth data. The algorithm and the weights determined during the training step comprise a model that can be used to make predictions from new data. This learning process generally improves with increasing amounts and quality of preclassified data used for training. The model weights are updated as new data are acquired and classified.

When developing an NN, two main steps are mandatory (Fig. 1). First, the NN is trained on a set of data that has been preclassified, generally by human experts. Training is an iterative process, in which the algorithm finds a set of weights that minimizes an error measure. Without getting into the details, this training process combines linear algebra, statistics, and differential calculus to minimize the error between the classifications assigned by the algorithm and classifications in ground truth data. Second, the trained NN, or model, is deployed to classify new data sets. The NN approach can be used to classify text, images, or other information. In this article, however, we will focus on classification of images, which is a machine vision application.

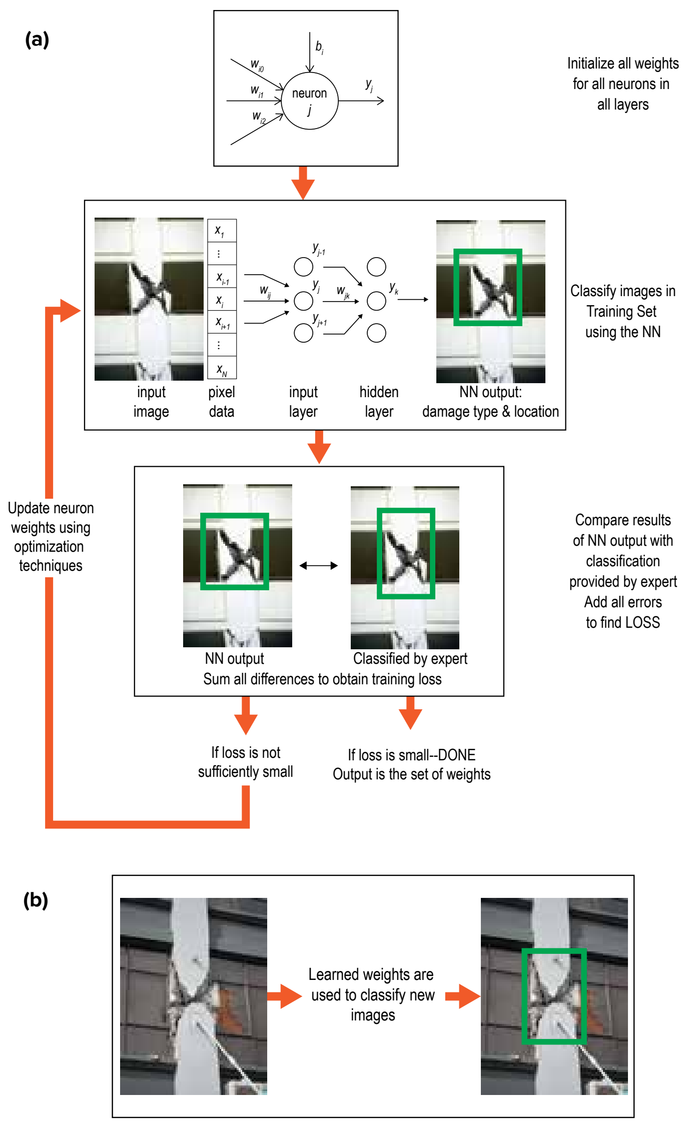

Fig. 1. Basic workflow for a DL algorithm designed to identify damage in images of structures: (a) in the training step, the algorithm sets internal parameters (weights) based on images tagged by an expert as showing damage or no damage; and (b) in the deployment step, the trained model is used to identify damage in new images

As stated previously, DL algorithms mimic the connectivity of biological neural systems. Although we do not exactly know how the human brain works, we do know that a collection of connected neurons can perform very complex tasks, even though a single neuron can do very little. The same can be said about the connected neurons in a DL algorithm. The neurons in a DL algorithm can mimic a biological neuron by "firing" when stimulated sufficiently by inputs from other neurons. We term this activation and the mathematical operators that determine the state of a neuron are termed activation functions.

DL algorithms are trained by iteratively making calculations forward and backward through the network. The training step in developing an NN is an iterative process that effectively calibrates a model. This is illustrated in Fig. 1(a).

During a forward pass, the training set is classified, or assigned a score, by the algorithm using the current network weights. During a backward pass, the weights are updated to improve the classification relative to the ground truth on the next iteration. The adjustments are made using loss and cost functions to measure the error between the classifications made by the algorithm and the classifications provided in the training set. Detailed descriptions of loss functions can be found in the literature (for example, refer to Reference 7).

Neurons and weights

For DL applications, a neuron k is a software function that takes an input and generates an output using an activation function (Fig. 2(a)). Each neuron k has a bias b_k and a set of weights, w_{jk}, associated with its connection to preceding neurons i. The bias provides a uniform offset to control the sensitivity of the learning process. The weights provide indications of the level of interaction between nodes. Together, they can be considered as analogous to the intercept value and the slope in the equation for a straight line. Whenever there is a change in the input x_i the output varies linearly. As a starting point, the weights are usually initialized to small arbitrary values. The weights within the NN will change during the iterative learning process.

Neurons are grouped in layers (Fig. 2(b)) that are connected with other layers of neurons. In fact, deep learning gets its name from the high number of layers used in DL algorithms. An NN is comprised of an input layer that reads input values and an output layer that produces one or more numbers that represent a certain classification. An NN also comprises multiple hidden layers (layers between input and output layers). In a fully connected NN, each neuron adds all the outputs of the previous layer's neurons together and applies an activation function, whose job is to pass to the next layer these additions only if it is above a threshold value (again, the activation function determines if the neuron will "fire"). In other words, if the signal from "upstream" neurons

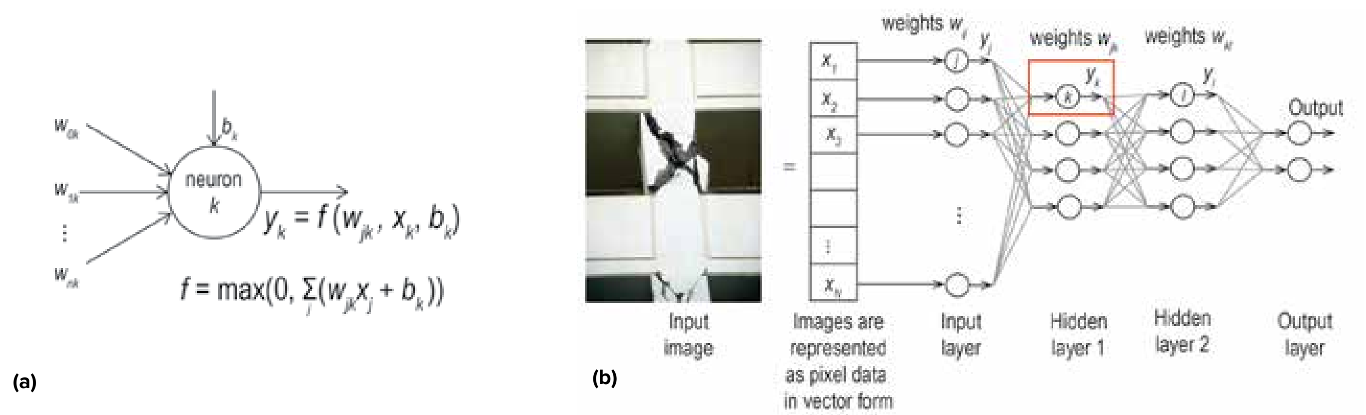

Fig. 2: Details of neurons and layers in an NN: (a) neuron *k*, with y_j input values and output y_k. For each neuron *k*, w_{jk} is the weight assigned to the neuron for each y_j; and (b) schematic of layers in an NN, showing the position of neuron *k* within the red box

is too small, the neuron will not translate input from the previous layers to the following layers. The activation function determines whether the output from a layer's neuron will identify and propagate an input. Some of the activation functions used in DL algorithms are discussed in Reference 8.

Training

During training, the weights and biases are adjusted for each neuron, allowing interconnected hidden layers to learn patterns from an input set. The number of neurons per hidden layer and the number of layers is chosen by the data engineer. The complexity of the model is usually based on some previously developed NN that was used to solve a similar problem. The number of neurons in the input layer is the same as the size of the input data. For example, if the input comprises 32 x 32-pixel greyscale images, the input layer will contain $32^2 = 1024$ neurons. Note that each pixel will have 256 tonal levels for a black-and-white image, and that the number of neurons in the input layer will triple if the input comprises red, green, and blue color images.

Successive hidden layers in NN algorithms have been observed to be capable of progressively identifying higher-level features. For example, the first hidden layer may identify contrast lines within images (Fig. 3).[9] The next hidden layer may then respond to associations of these edges, with neuron connections that are sensitive to respectively identifying noses, eyes, ears, and mouths, for example. A deeper layer might then have neurons that are activated by the presence of a nose, two eyes, two ears, and a mouth (in other words, neurons in this layer would respond positively to a face). By connecting many layers, we can create systems that can learn to identify complex objects in an image (Fig. 3).

As previously stated, training the NN is an iterative process, with the goal of minimizing the classification errors associated with the training set (ground truth). Massive numbers of weights and biases may be adjusted during the process, even if the algorithm provides only a binary (true or false) classification. For example, if the input is a 32 x 32-pixel

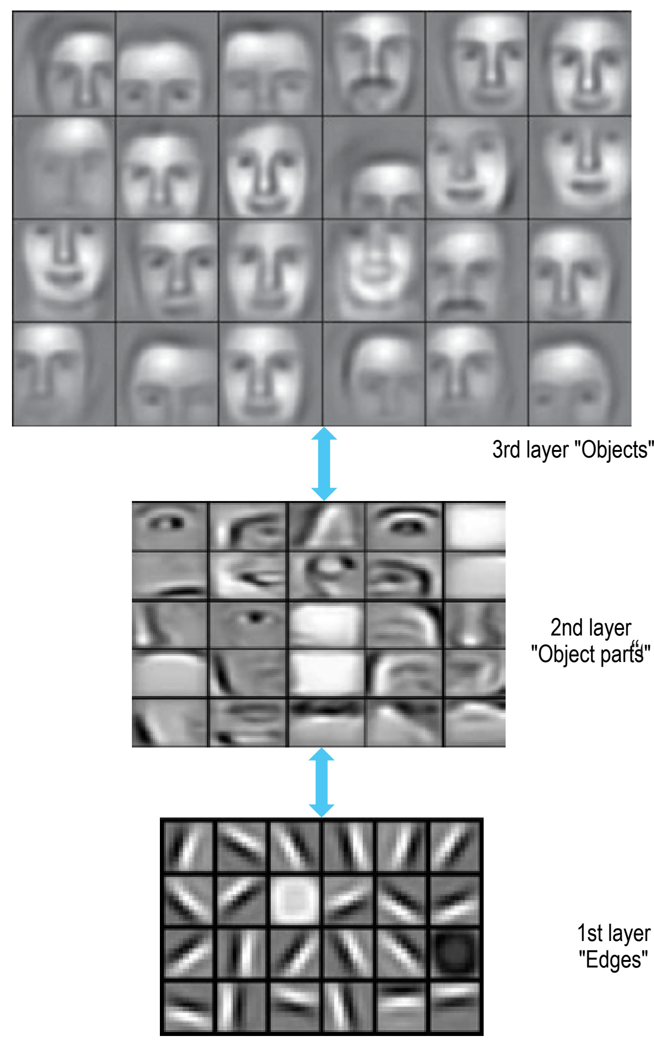

Fig. 3: Layers tend to learn progressively more complex patterns. As shown in Reference 9, inputs comprising photos of faces can be categorized by layers that are activated by changes in contrast to define edges and parts of objects. A following layer within the NN is activated by the objects—in this case, faces

greyscale image, the network will require 1024 neurons in each hidden layer to be fully connected (in a fully connected layer, all neurons in that layer are connected to all neurons in the preceding and succeeding layers in the network). If the network configuration has 10 fully connected hidden layers, over 855,000 weights must be adjusted during each training step, and each training step will include data for every image in the training set. Similarly, millions of weights must be learned for a DL algorithm with hundreds of layers and input images in the range of 1000 x 1000 pixels. Thus, DL algorithms can take hours to train, even using parallel processing accelerators such as graphics processing units (GPUs).

While a NN with many parameters can fit a training set data very accurately, this does not necessarily mean that this is a good solution for an implementation. Such a trained NN may fail to generalize and thus will fail to correctly classify new input images that differ from the images in the training set. This problem is called overfitting. Refer to Reference 8 for discussions of some of the methods used to avoid overfitting.

Classification errors associated with the training set are determined using a loss function, which can be considered a surface in multi-dimensional space. This function is minimized using a very well-known optimization technique called gradient descent (GD),[10] which finds changes in weights that result in the steepest descent within the loss function to minimize the loss function.

This can be visualized using the function for the straight-line $y = a + bx$, where the slope b of the function is the rate of change (gradient), also given as the derivative of the function. In the more general problem associated with DL, the gradient is the generalization of the slope for functions with a vector of input dimensions, and it must be found using partial derivatives. While GD determines the direction in which the function has the steepest rate of change, the data engineer must determine how far the program should step. That is, the team developing the DL algorithm must heuristically set the learning rate for the algorithm. If the steps are too large, the algorithm may overshoot the optimal solution. If the steps are too small, the algorithm will take too long to find a solution or the algorithm might get stuck in a local minimum.

Because modern DL algorithms have millions of weights, calculation of the GD and the updates of the weights is so computationally intensive that DL algorithms were long considered too slow and difficult to train. This changed when Rumelhart, Hinton, and Williams described how to improve the convergence rate using backpropagation.[11]

Backpropagation is based on the chain rule and allows the calculation of the GD and the update of the input weights layer by layer. More details about back propagation are discussed in References 10 to 13.

The benefit of backpropagation is that the derivatives can be calculated recursively and relatively quickly. Once the derivatives have been found, the weight on each neuron is adjusted proportionally, according to how fast that weight will lower the loss function. The output of the classifier and the gradients for each one of the neurons can be calculated to minimize the loss function in one step. After this update is finished, the forward and backward passes are repeated until the loss value has satisfied a defined minimum. The output of the final training step will be the set of weights that minimize the loss function.

Classification Competition

The Pacific Earthquake Engineering Research Center (PEER) has organized the first image-based structural damage identification competition, the PEER Hub ImageNet (PHI) Challenge. Contestants will receive training and testing data sets that have been labeled for classifications that include:

- Scene level (pixel, object, or structural);
- Damage condition (yes or no);
- Spalling condition (yes or no);
- Material type (steel or other);
- Collapse state (none, partial, or full);
- Component type (beam, column, wall, or other);
- Damage level (none, minor, moderate, or heavy); and
- Damage type (none, flexural, shear, or combined).

Competitors will test the classification accuracy of their algorithms at three levels of difficulty. The competition is scheduled to start on August 23 and close on November 25, 2018. The winner will be announced on December 15, 2018.

Visit **http://apps.peer.berkeley.edu/phichallenge/** for more information.

Deployment or inference

The deployment step is much simpler than the training step. Once the training step is finished, the result is a set of weights that when multiplied by the input pixels will create the automatic classification (Fig. 1), this step mainly consists in floating point multiplications and does not need sophisticated hardware for intensive computation. Usually, when a new NN is trained we use a computer that has one or more GPUs, but the deployment can be executed by much simpler hardware, including smartphones, tablets, and smaller computing devices.

Convolutional Neural Networks

Convolutional neural networks (CNN) are a category of NN that have proven very effective in areas such as image recognition and classification. CNN derive their name from the "convolution" operator, which reduces the number of weights required to classify the input. Compared to a conventional NN, CNN networks reduce the computation in the hidden layers by not requiring them all to be fully connected.

An image is a two-dimensional (2-D) matrix of pixel values that range in values from 0 to 255, a convolutional filter is also a 2-D matrix, usually of odd size (for example, 3 x 3 or 5 x 5). A convolution operation is a mathematical operation obtained by "sliding" (indexing) the convolutional filter over every element in the input image matrix. At each position of the convolution filter the values in the filter matrix are multiplied with the near neighbors in the image matrix and the products are summed (Fig. 4). Convolutions have been traditionally used in image processing to detect edges and gradients. CNN algorithms are designed to learn the values of these convolution filters on their own during the training process. A common CNN configuration is illustrated in Fig. 5.

In general, a CNN consists of a combination of the following layers:

- INPUT layer, which comprises raw pixel values of an input image;
- CONV layer, which will compute the

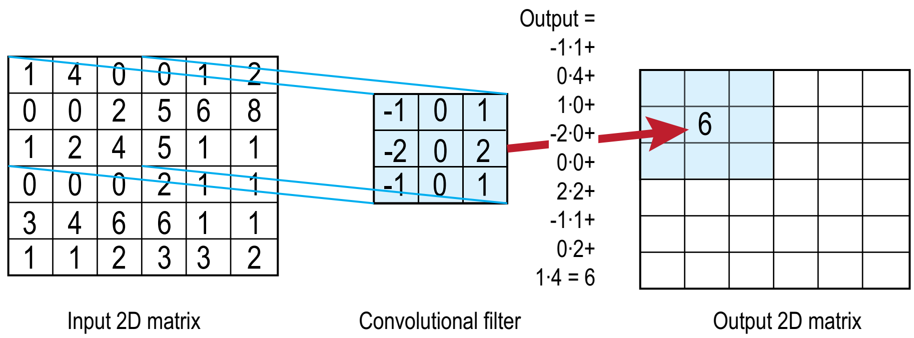

Fig. 4: An example of a convolution operation

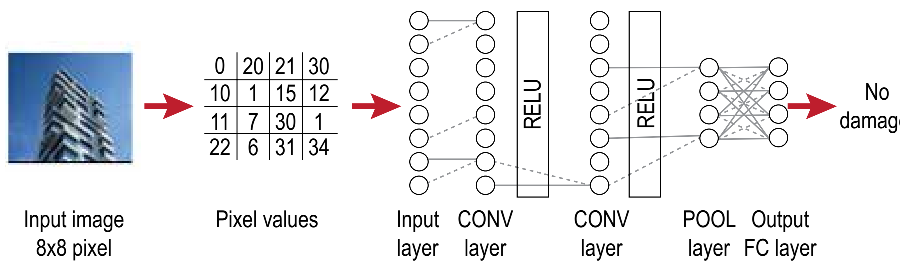

Fig. 5: A schematic of a CNN configuration

Fig. 6: Bounding box classification results: shear damage to short/captive column

output of neurons that are connected to local regions in the inputs (RELU is short for rectified linear unit, an activation function used in the computations);
- POOL layer, which will perform a downsampling operation along the spatial dimensions (width, height); and
- Fully Connected Output layer, which will compute the class scores for each category the algorithm is earning to recognize.

The first work that widely popularized convolutional networks in computer vision was the AlexNet.[14] The AlexNet was submitted to the ImageNet challenge in 2012,[15] and it significantly outperformed previous implementations. In fact, it did so well, most of the DL algorithms for object classification are now CNN. CNN generalize well and can correctly classify different objects if enough preclassified input data can be provided for training.

When creating a new NN to classify a new object, the data engineer must decide the number of layers, the number of neurons per layer, the learning rate, and numerous other parameters. However, in practice, most practitioners reuse previously trained CNN algorithms—they modify only a few of the parameters for a new data set. This technique is called transfer learning.

One of the main goals of DL is to be able to automatically detect objects on image/video. This is based on the premise that if a human can see the difference and manually tag/recognize an object, then a DL algorithm should also be able to detect the same features and patterns needed to identify the object. In our application, the object to identify is a damage/structure pair on images taken after an earthquake. We have created a DL algorithm capable of recognizing earthquake-induced damage on concrete buildings. For this process, we use the object detection application programming interface for Tensorflow,[15] a public domain software package. Our implementation uses the AlexNet configuration.[14] The steps to develop the DL for damage/structure defect detection are provided in Reference 15. The DL algorithm is capable of drawing a bounding box around short/captive column with shear damage, with an accuracy of 77%. Figure 6 presents a few examples of images the algorithm correctly tagged for this damage type.

There are a few challenges with training for specific damage-structural member pairs that may explain the current level of accuracy. First, finding 200 high-quality images from reputable sources that accurately represent earthquake loading damage is a time-intensive process. Second, the research team is currently dependent on images tagged by only one expert. There is a need to use multiple experts to provide verification of the ground truth set. Nevertheless, the current level of accuracy is rather promising and we believe that with a larger set of training images labeled by at least two experts, the DL algorithm's tagging performance would be comparable to a human expert. Output images would have additional metadata that includes the damage-structural member types and its locations in the images, which would enable large structural reconnaissance image repositories to become searchable using specific terms.

Because this work is in the preliminary stages, we welcome contributions from experts in the field to help build a comprehensive database and implement and test the model.

Summary and Application

In this article, we presented an introduction to deep learning; specifically described is the use of a convolutional neural network and the supervised learning process. This approach is currently being applied to train a model that will enable professional structural engineers to automatically detect types of earthquake damage. Initial results are promising. Output images would have additional metadata that includes the damage-structural member types and their locations in the images, which would enable large structural reconnaissance image repositories to become searchable using specific terms.

As mentioned previously, computer vision and deep learning have advanced to the stage that they can make substantial improvement in many fields. DL solutions are currently being researched and implemented to solve civil engineering related problems, including autonomous inspection and inventory of civil infrastructure projects.

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Selected for reader interest by the editors.

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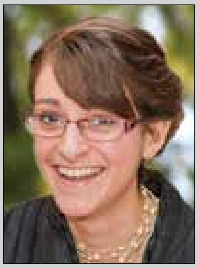

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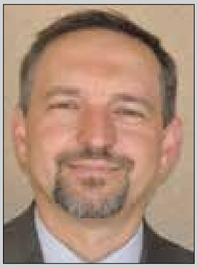

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