texts are fixed. The novel approach introduced in this paper eliminates such an assumption. The algorithm is based on the observation that different people's handwritings are visually distinctive, and a global approach based on textures analysis can be adopted. Our approach is therefore text independent.

***Table 3: Identification accuracy of the GSCM technique under WED***

| Distances | Set A | Set B |
|---|---|---|
| d=1,2,3,4,5 | 59.8 | 52.2 |
| d=1,2,3 | **63.6** | 58.8 |
| d=2,3,4 | 53.5 | 50.8 |
| d=3,4,5 | 45.6 | 46.0 |
| d=1,2 | **56.0** | 56.4 |
| d=4,5 | 43.2 | 46.4 |
| d=1 | 59.4 | 59.5 |
| d=4 | 41.8 | 46.0 |

***Table 4: Identification accuracy of the GSCM technique under K-NN***

| Distances | Set A | Set B |
|---|---|---|
| d=1,2,3,4,5 | 43.3 | 60.5 |
| d=1,2,3 | 45.3 | **68.0** |
| d=2,3,4 | 40.3 | 57.0 |
| d=3,4,5 | 39.7 | 39.7 |
| d=1,2 | 37.7 | **74.0** |
| d=4,5 | 37.3 | 53.5 |
| d=1 | 44.3 | 65.5 |
| d=4 | 38.3 | 58.5 |

A number of experiments have been conducted. The experiments use 20 different writer classes. Features were extracted from handwriting images using the multichannel Gabor filtering technique and the grey scale co-occurrence matrix (GSCM) technique. Identification was performed using two different classifiers (the weighted Euclidean distance and the K-nearest neighbour (K-NN) classifiers). The results achieved were very promising, and an identification accuracy as high as 95.3% was obtained. The K-NN classifier gave poor results compared to the other classifier.

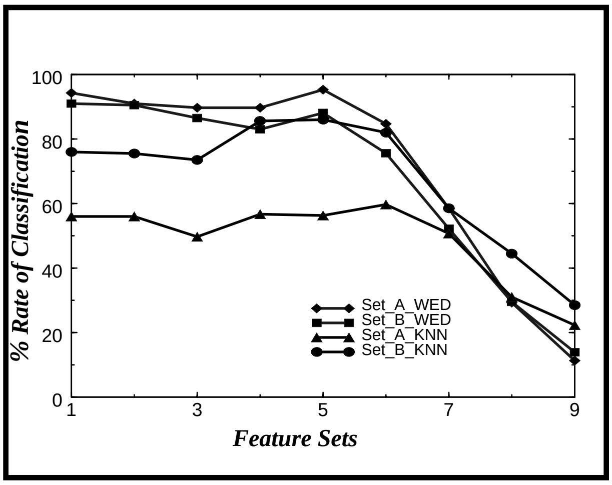


***FIGURE 2. Results from Gabor filter using the WED & KNN classifiers***

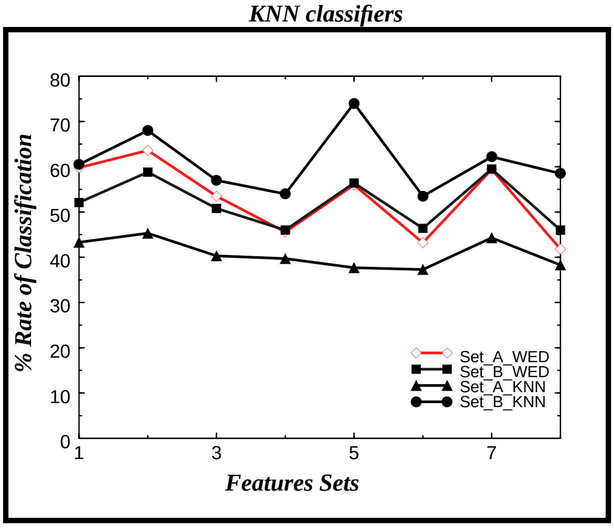


***FIGURE 3. Results from Gabor filter using the WED & KNN classifiers***

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an A4 page, scanned using a HP ScanJet4c in custom mode with extra heavy lighting, at a resolution of 150dpi.

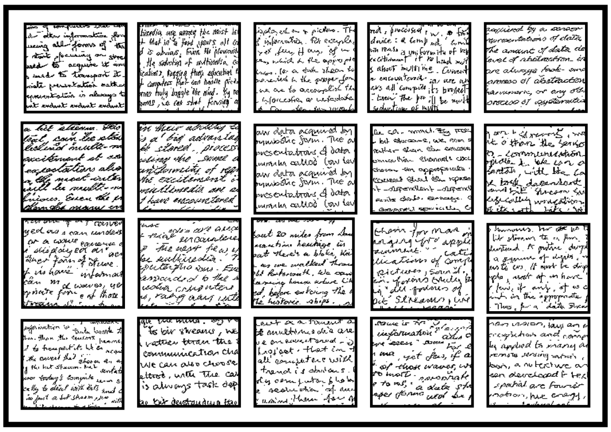

***FIGURE 1. Examples of handwriting of 20 different people***

Each sample block was of 128x128 pixels. The sample images were divided first into 10 training and 15 test images per writer (Set A) followed by 15 training and 10 test images (Set B). Images in the test sets did not appear in the training sets. Testing was conducted using different combinations of features under both classifiers.

***Table 1: Identification accuracy of the Gabor filtering technique under WED***

| Features | Set A | Set B |
|---|---|---|
| All | **94.3** | 91.0 |
| SD | 91.0 | 90.0 |
| Mean | 89.7 | 86.5 |
| Mean at f=16,32 | 89.7 | 83.0 |
| All at f=16,32 | **95.3** | 88.1 |
| All at f=32 | 84.7 | 75.6 |
| All at f=16 | 58.1 | 52.2 |
| All at f=8 | 29.3 | 29.5 |
| All at f=4 | 11.3 | 13.9 |

Identification results are summarised in Tables1-4. In Tables 1-2, features were extracted using the channels at f = 4,8,16,32 and $\theta = 0°, 45°, 90°, 135°$ (hence there were a total of 32 features); and for Tables 3-4, features were extracted using distances at d=1,2,3,4,5 and directions $\alpha = 0°, 45°, 90° and 135°$ (there were a total of 60 features).

Tables1-2 show the results of the multichannel Gabor filter features using the two classifiers. When the WED classifier was used, generally higher identification accuracies were observed (especially for Set A). For example, a classification rate of 94.3% was obtained when all 32 features were used (for Set A). Results of 95.3% were observed when f=32 and 16 were chosen.

***Table 2: Identification accuracy of the Gabor filtering technique under K-NN***

| Features | Set A | Set B |
|---|---|---|
| All | 56.0 | **76.0** |
| SD | 56.0 | 75.5 |
| Mean | 49.7 | 73.5 |
| Mean at f=16,32 | 56.7 | 85.6 |
| All at f=16,32 | 56.3 | **86.0** |
| All at f=32 | 59.7 | 82.0 |
| All at f=16 | 50.7 | 58.5 |
| All at f=8 | 31.0 | 44.5 |
| All at f=4 | 22.3 | 28.5 |

Under the K-NN classifier, a classification as high as 76.0% was achieved, when all 32 features were used (for Set B). The best results (86.0%) under the K-NN were achieved when the frequencies of f=16 and 32 were used (for set B). For easier comparison Fig. 2 shows the plots of the identification accuracies for the Gabor filtering features under both classifiers, where the features sets are in the same order as in the Tables 1-2 (e.g. features set 1 for all features; set 2 for all SD features; etc.).

Tables 3-4 show the classification rates for the GSCM approach for each classifiers. Here, the results can be seen to be much poorer than those for the Gabor filter method. This observation is consistent with the findings in [6,8]. Fig. 3 shows the plots of the identification accuracies for the GSCM features under both classifiers. Again the feature sets are in the same order as in Table 3-4. The best results (in shaded box) show that only 63.6% of the images were identified correctly, when using the WED classifier. Here, 36 texture features were used.

In comparison, a classification rate of 74.0% is obtained when the K-NN classifier was used (with a total of 24 texture features). It is also noted that under the K-NN performance in set B (using 10 testing images) is far better than Set A. This was not the case for the WED classifier, where set A gave poor results. It is clear that for both sets of features (Gabor filtering and GSCM) the WED classifier gives better performance than K-NN classifier. It can also be seen that the identification accuracy is much higher when the Gabor filter technique is used. Poorer results are given when the GSCM method is conducted.

## 8. Conclusion

We have described a new approach towards handwriting based personal identification. Most existing approaches make an implicit assumption that handwritten spacing between lines/words and margins are set to predefined size by means of text padding. Finally, random non-overlapping blocks (of $128 \times 128$ pixels) are extracted from the normalised image. Texture analysis is applied to these blocks. Further details on normalisation may be found in [6].

## 3. Writer Features Extraction

In principle any texture analysis technique can be applied to extract features from each uniform block of handwritings described above. Here two established methods are implemented to obtain texture features, namely the multichannel Gabor filtering technique [8] and the grey scale co-occurrence matrix (GSCM) [9]. The former is one of the most popular methods and well recognised, and the latter is often used as a benchmark in texture analysis [9].

### 3.1 Gabor Filtering

The multichannel Gabor filtering technique is inspired by the psychophysical findings that the processing of pictorial information in the human visual cortex involves a set of parallel and quasi-independent mechanisms or cortical channels which can be modelled by bandpass filters.

A simple computational model for the cortical channels is described in [8]. Briefly stated, each cortical channel is modelled by a pair of Gabor filters $h_e(x, y; f, \theta)$ and $h_o(x, y; f, \theta)$. The two Gabor filters are of opposite symmetry and are given by

$$\begin{cases} h_e(x, y; f, \theta) = g(x, y)\cos(2\pi f(x\cos\theta + y\sin\theta)) \\ \\ h_o(x, y; f, \theta) = g(x, y)\sin(2\pi f(x\cos\theta + y\sin\theta)) \end{cases} \tag{1}$$

where $g(x, y)$ is a 2-D Gaussian function, $f$ and $\theta$ are the radial frequency and orientation which define the location of the channel in the frequency plane. Commonly used frequencies are of power 2. In [8] it has been shown that for any image of size $N \times N$, the important frequency components are within $f \leq \frac{N}{4}$ cycles/degree. In this paper we use frequencies of 4, 8, 16 and 32 cycles/degree.

For each central frequency *f*, filtering is performed at $\theta = 0°, 45°, 90°$ and $135°$. This leads to a total of 16 output images (4 for each frequency), from which the writes' features are extracted. These features are the mean and the standard deviation of each output image. Therefore, 32 features per input image are calculated. Testing was performed by using either all 32 features or various subsets (e.g., features associated with a particular radial frequency).

### 3.2 Grey Scale Co-occurrence Matrices (GSCM)

GSCMs are also considered. Generally speaking, GSCMs are computationally expensive. For an image represented using $N$ grey levels, each GSCM is of size $N \times N$. In the case of binary handwriting images, we have only two grey levels. Therefore, it is reasonable to use the GSCM technique. In this paper, GSCMs were constructed for five distances $(d = 1, 2, 3, 4, 5)$ and four directions $\alpha = (0°, 45°, 90°, 135°)$. This gives each input handwriting image 20 matrices of dimension $2 \times 2$. When the size of the GSCM is too large to allow the direct use of matrix elements, measurements such as energy, entropy, contrast and correlation are computed from the matrix and used as features [9]. For each $2 \times 2$ GSCM derived from a binary handwriting image, there are only 3 independent values due to the diagonal symmetry. The 3 values are used directly as features. Then, we have 60 (= $2 \times 3$) features per handwriting image.

## 4. Writer Identification

Here two classifiers were considered, namely the weighted Euclidean distance classifier (WED) and K-NN classifier. Representative features for each writer are determined from the features extracted from training handwriting texts of the writer. Then, for an input handwritten text block by an unknown writer, similar feature extraction operations are carried out. The extracted features are then compared with the representative features of a set of known writers. The writer of the handwriting is identified as Writer $K$ by the WED classifier *iff* the following distance function is a minimum at $K$:

$$d(k) = \sum_{n=1}^{N} \frac{(f_n - f_n^{(k)})^2}{(v_n^{(k)})^2} \tag{2}$$

where $f_n$ is the $n^{th}$ feature of the input document, and $f_n^{(k)}$ and $v_n^{(k)}$ are the sample mean and sample standard deviation of the $n^{th}$ feature of writer $k$ respectively. Both the (WED) and the K-NN classifiers have been used. Other decision rules are equally applicable here.

## 6. Experimental Results

A number of experiments were carried out to show the effectiveness of the proposed algorithms. Twenty people were chosen. Examples of handwritings by these people are shown in Fig.1. For the purpose of the classification experiments, 25 non-overlapping handwriting blocks were extracted for each person. Each sample was selected from

# Personal Identification Based on Handwriting

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### Abstract

*Many techniques have been reported for handwriting-based writer identification. Most techniques assume that the written text is fixed (e.g., in signature verification). In this paper we attempt to eliminate this assumption by presenting a novel algorithm for automatic text-independent writer identification. Given that the handwriting of different people can often be visually distinctive, we take a global approach based on texture analysis, where each writer's handwriting is regarded as a different texture. In principle this allows us to apply any standard texture recognition algorithm for the task (e.g., the multi-channel Gabor filtering technique). Results of 95.0% accuracy on the classification of 300 test documents from 20 writers are very promising. The method is shown to be robust to noise and contents.*

***Keywords: Personal identification, Writer identification, Texture analysis, Gabor filters, Handwriting processing, Document image processing.***

## 1. Introduction

Signature verification has been an active research topic for several decades in the image processing and pattern recognition community [1]. Despite continuous effort, signature verification remains a challenging issue. It provides a way of identifying the writer in security and related applications. It requires the writer to write the same fixed text. In this sense, signature verification may also be called text-dependent writer verification (which is a special case of text-dependent writer identification where more than one writer is considered). In practice the requirement and the use of fixed text makes writer verification prone to forgery. Furthermore text-dependent writer identification is inappropriate for many important practical applications, e.g. the identification of the writers of archived handwritten documents, crime suspect identification in forensic sciences etc. In these applications, the writer is often identified by professional handwriting examiners. Although human intervention in text-independent writer identification has been effective, it is costly and prone to fatigue.

Research into writer identification has been focused on two streams, off-line and on-line writer identification. This paper focuses only on the off-line part. Off-line systems are based on the use of computer image processing and pattern recognition techniques. There are two main approaches in the off-line method, text-dependent and text-independent. Our work is a text-independent approach where a texture analysis technique is introduced. Similar work has been proposed by Kuckuck [2], where a Fourier transform technique is used.

We use multichannel spatial filtering techniques to extract texture features from a handwritten text block. There are many available filters in the multichannel technique. Gabor filters are used since they have proven to be successful in extracting features for similar applications [3,4,5,6,7]. We have also used grey scale co-occurrence matrices (GSCM) for feature extraction. For classification two classifiers are adopted, namely the weighted Euclidean distance (WED) and the K-NN classifiers. The subsequent sections describe the normalisation of the handwriting images, the extraction of writer features, the experimental results and finally the conclusions.

## 2. Normalisation of Handwriting Images

Texture analysis cannot be applied directly to handwriting images, as texture is affected by different word spacing, varying line spacing, etc. The influence of such factors is minimised by a normalisation stage. The input to this stage is a binary image of any handwritten document. The handwriting may contain lines of different point size and different spacings between lines, words and characters. The normalisation is done as follows. First, text lines are located using the horizontal projection profile [6]. Then,