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PRINT-TO-EDGE REGISTRATION APPLICATION FOR BANKNOTES

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ABSTRACT

Spatial transforms and fuzzy pattern classification with unimodal potential functions are established in signal processing. They have proved to be excellent tools in feature extraction and classification. In this paper we present a concept on an image processing and classification scheme for a print-to-edge registration application. The application describes the position detection of objects in banknotes. The scheme is straightforward and therefore well suited for industrial applications. Furthermore, it can be applied to other applications. An implementation on one field programmable gate array (FPGA) will be proposed.

1. INTRODUCTION

Object recognition is of main interest in the field of image processing and pattern recognition in industry automation. In this paper a scheme for high speed pattern recognition which is applied to banknote cutting edge registration and positioning, is proposed. To our best knowledge this strategy was not published before [9]. In banknote printing usually all production steps are controlled by optical inspection systems [4], except for the last step, the cutting and sorting of banknote sheets into bundles of notes. The bundles contain 100 banknotes; 10 bundles are packed into one stack. This stack is feed into a rotary optical counting machine for quantity verification. As this process needs approx. 5 seconds, the inspection time frame for one note is approx. 5 milliseconds. The main task in all cutting devices is the verification of the correct cutting of the notes' edges in respect to the print. Due to the fact that the counting machine is equipped with an optical path, an adequate illumination and a high speed CMOS camera, which is able to grab up to 250 images per second in partial scan mode, the edges and the print can be scanned in a time frame of the above-mentioned 5 milliseconds. For the print-to-edge registration it is necessary to detect the edges, which can be done with a standard edge detector as the amplitude difference between the banknote and the background is large enough. Getting the position information for the print itself needs more sophisticated concepts. Of course, correlation methods can be used. However, as speed and image dynamics play an important role [8], we propose the comparison of local spectra to obtain a similarity measure between a reference object and an unknown pattern image. For various practical image processing and pattern recognition cases in an industrial environment, it is incidental that different process and signal distortions can occur. Therefore, the similarity measure is designed as a fuzzy pattern classifier, which is not applied on a pixel base tough on spectra of different simple non-sinusoid transform classes [7]. The non-sinusoid transforms allow a fast radix-2 calculation of the transform matrices. Furthermore, their coefficients are real. As a benchmark transform the Discrete Fourier Transform (*DFT*) in form of a radix-2 Fast Fourier Transform (*FFT*) was applied.

Since the optical system grabs only a small stripe (image stripe, height approx. 1.4 mm, 36 pixels) of the banknote (cf. figure 1) the reference image is part of a scanned banknote. In the scan area of the reference a portion of the banknote image is searched. The separability properties of nonlinear transforms are generally speaking incomplete. Therefore it is obvious to use group theory based methods to improve the separability properties [10, 11]. In this paper we propose the application of a simplified scheme for pattern recognition and classification scheme.

2. TRANSFORMS

We have applied different non-sinusoid transforms which serve as pattern generator for the fuzzy pattern classifier.

2.1 Generalized Circular Transforms

Generalized Circular Transforms (*GCT*) have some properties which are useful for the analysis of transient *and* periodic signals [6]. For details regarding the *generalized characteristic* and *generalized circular* matrices, we refer to other publications [7]. All transforms have in common that they use an amplitude spectrum $\boldsymbol{G}$ with $(\mathrm{ld}(N)+1)^2$ coefficients in the two-dimensional (2-D) case. This spectrum is called group spectrum because different group invariant

Figure 1 – Part of a banknote with typ. scan area and image stripe

features are generated by adaptation of the transform matrix. We use an absolute value determination to obtain the spectrum. This spectrum is much easier to implement in Field Programmable Gate Arrays (*FPGAs*) than Fast Fourier Transform spectrum based on complex functions.

2.2 Walsh-Hadamard Transform

In addition to the GCT the Walsh-Hadamard Transform (*WHT*) was applied [1]. This transform is sometimes called BIFORE transform (*Binary Fourier Representation*). While the DFT bases are discrete sinusoids with harmonic frequencies, the BIFORE bases are Walsh functions in natural order, which can be generated by a Hadamard matrix. Since the Walsh functions are square waves, they consist of only two values, namely -1 and +1. The WHT is well known and can also be processed as a non-sinusoid fast transform. Furthermore, a power spectrum with $(\mathrm{ld}(N)+1)^2$ coefficients is achievable. Since only real number operations are involved, the transform saves computing time in comparison to the FFT.

3. PREPROCESSING

Figure 2 shows a scanned stripe of a banknote and the reference image with the measurements, which are necessary for the print-to-edge registration. It can be seen that the contrast is not optimal. The grey scale contrast is in a range of 60 - 100 grey values (8 bits resolution). Also a shading effect is visible in the outer areas of the image. Furthermore, the image is superimposed with noise which is presumably quantum noise due to the fact of that the light energy is not high enough. Therefore, a constraint Wiener filter, a shading correction and a contrast optimisation was implemented in the signal chain of the image processing part.

4. CLASSIFICATION

The *Fuzzy-Pattern-Classification* (FPC) is a useful approach for modelling complex systems [3] and classifying noisy data [7]. Accordingly, the feature vector has to be stabilized and correctly classified without exact knowledge of different stochastic processes [4]. Therefore, a simplified classifier model [3] will be used here which is well suited for industrial applications. It was recently used for bank note inspection because of better classification results compared to other classifiers [8]. It is based on a concept, which allows the simultaneous calculation and aggregation of distance measures (cf. eq. 1). FPC is based on membership

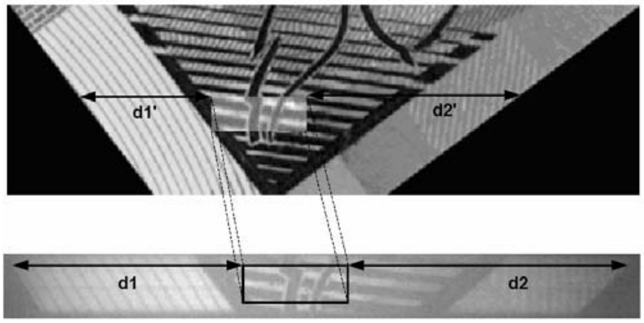

Figure 2 – Example of a reference image (top) and scanned image stripe (bottom) with an indication of the typical measurements

functions $\mu(m;\boldsymbol{p})$. They are modelled as unimodal potential functions [3, 7]. The distance measure can be interpreted as a generalised Minkowski distance. The behaviour of the feature m is described with the appropriate parameter vector $\boldsymbol{p}=(m_0,C,D)^T$ (cf. eq. 2). The membership function which is used for the hardware implementation is determined as follows:

$$\mu(\boldsymbol{m};\, {}^{k}\boldsymbol{p}) = 2^{-\frac{1}{M}\sum\limits_{i=0}^{M-1} d(m_i;\, {}^{i}\boldsymbol{p})}, \quad 0 \le \mu(\circ) \le 1, \qquad (1)$$

with the difference measure

$$d(m;\boldsymbol{p}) = \left(\frac{|m-m_0|}{C}\right)^D . \qquad (2)$$

The advantage of those functions is their adaptation on different inputs by a learning process or by an expert's tuning with linguistic modifiers. Details can be found in [7]. As the amount of learning samples is normally low, statistical classifiers based on the Bayes framework perform inefficient.

5. EXPERIMENTAL RESULTS

Different banknote types have been tested from a production run in our first tests. It can be said that the window size is of major importance for all transforms. Furthermore, it has to be pointed out that the position of the reference window is critical in the sense that the pattern must be unique.

The following fast transforms were analysed:

- Sinusoid transform
  - Fourier Transform (FFT)

- Non-sinusoid transforms
  - Generalized Circular Transforms [7]
    - Square Wave Transform (SWT)
    - Generalized Circular Transform A1 (GCTA1)
    - Generalized Circular Transform p2 (GCTp2)
  - Walsh-Hadamard Transform (WHT)

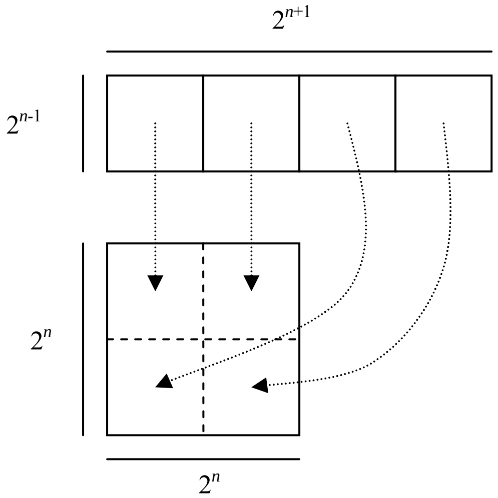

Figure 3 – Concatenation of scan window for the transforms

Due to the fact that radix-2 fast transforms are used only with window sizes of 2^n x 2^n, $n \in N$ are possible. The banknote stripe allows a maximum size of $n = 5$ in vertical direction. Therefore, since we used the windows sizes 32 x 32, 16 x 64 and 32 x 128, a concatenation of the scan window is necessary. As only the spectral differences are of interest a concatenation scheme as showed in figure 3 is permitted.

It has to be mentioned that in many cases illumination changes can be eliminated if the average value as a feature is not included. Furthermore, it has to be mentioned that all reference spectra and the search spectra are normalized by dividing all coefficients by the largest coefficient. The direct illuminated and grabbed images represent the system's robustness to reflections and shadings.

In the following, we present the results for banknotes with a certain denomination, which is in circulation. As the banknote shows periodical guilloches the detection of the correct position is not elementary, because the local spectra are similar. In one bundle 72 notes were identified with an overall print-to-edge register deviation, which is equal to or greater than 1.4 mm. This means that the image stripe, which is grabbed, must be completely different from other images. The reference image (cf. figure 4) of the size of 220 x 220 pixels is used for the similarity detection. As explained above three versions of window sizes were applied to the process.

5.1 Transform Analysis

Five sinusoid and non-sinusoid transforms were analysed. The criteria were defined as follows: Type – sinusoid or non-sinusoid, Computeral Complexity – order number on real or complex number, Frame – structure of the basis vectors, Support – local or global support of basis vectors, Matrix Elements – number range of the transform matrix elements. All transforms were applied on different window sizes as explained above. It is worth knowing that for

Figure 4 – Scan area in the reference image 220 x 220 pixels

the FFT the best results were achieved by using only the imaginary part of the spectrum, because of its phase sensitivity. The transform's properties are summarised in table 1.

Table 1 – Properties of different transforms

Size	Type	Computeral Complexity	Frame	Support	Matrix Elements
FFT	sinusoid	O(N ld(N))	orthogonal	global	Complex, ≤ 1
SWT	non-sinusoid	O(N ld(N))	non-orthogonal	global	-1, and +1
GCTA1	non-sinusoid	O(N)	non-orthogonal	local	-1, 0 and +1
GCTp2	non-sinusoid	O(N ld(N))	non-orthogonal	global	2^n and -2^n, $n \in N$
WHT	non-sinusoid	O(N ld(N))	orthogonal	global	-1, and +1

Generally it can be said that the window 32 x 32 seems too small to generate non-similar spectra in the search process. The window 16 x 64 obviously comprises enough information for 100 % detection in general, whereas only the WHT can generate 100 % recognition rates of the correct positions for the window 32 x 128 (cf. figure 5). It seems that the vertical window size is too large. In some cases, part of the outer mechanical stripe areas can be seen in the image. Obviously the WHT can distinguish the spectra, because of the equilibrium between detection of high-sequency components and orthogonality of the base vectors. It has also to be mentioned that the GCTA1 reacts strongly on high-sequency components (local support), which causes problems in the similarity detection. This effect can not be absorbed by the fuzzy classifier. Table 2 summarizes the recognition results for the above mentioned transforms. Furthermore, the results for the position detection with the normalized cross-correlation function (*CCF*) method [5] are shown.

Table 2 – Comparison of recognition rates for different transforms and CCF in percentage

Size	FFT	SWT	GCTA1	GCTp2	WHT	CCF
32 x 32	< 50	< 50	< 50	< 50	97	< 50
16 x 64	100	99	100	97	100	100
32 x 128	90	88	90	88	100	80

5.2 Computing Time

The major part of the computation time (approx. 90 %) is assigned to the transform. In the reference image a large number of positioning steps have to be executed. In this case we have 35,344 for 32 x 32; 31,842 for 16 x 64 and 17,296 for 32 x 128 to reach all possible positions in the reference image (cf. figure 5). Hence, the effective calculation is essential for the implementation. We propose a concatenation of the 2-D input matrix to a 1-D vector of the length N^2 and the implementation of a parallel radix-2 transform matrix which results in a calculation time of O(2 ld(N)). However, the amount of butterfly-processors is of O(N/2 ld(N)). Due to the fact that non-sinusoid transforms achieve good results under practical aspects, the butterfly-processors are elementary, especially in the case of the GCTA1 and WHT. Taking into account the above mentioned numbers, the following execution times per banknote are obtainable:

- Window 32 x 32: approx. 8 ms
- Window 16 x 64: approx. 7 ms
- Window 32 x 128: approx. 5 ms

We assumed the use of an FPGA of type ALTERA Stratix II [2] with a clock rate of 50 MHz. The transform implementation is feasible. It can be deduced that real time processing is only possible if the reference image size is reduced or the clock rate is increased. However, even if real time processing is not possible, some seconds delay is acceptable for the application.

6. CONCLUSION

We have presented an algorithmic concept based on different transforms and modified fuzzy pattern classification for pattern recognition in a banknote print-to-edge registration application. It was shown that different transforms can be applied to the application, whereas the non-sinusoid transforms, especially the WHT, performed excellently for the position detection. Obviously this transform can distinguish the spectra because of the equilibrium between detection of high-sequency components and orthogonality of the base vectors. Furthermore, an implementation on one Field Programmable Gate Array seems to be possible. We propose a 2-D to 1-D concatenation and the use of a 1-D transform, because the transforms sizes are applicable for a 1-D transform. Due to the fact that non-sinusoid transform perform well, they seem to be the best choice. As the hardware complexity is moderate for those transforms, they are applicable in the application.

Figure 5 – Reference image with superimposed recognized scan image with the size 32 x 128 at the position p

7. REFERENCES

[1] N. Ahmed, K.R. Rao, A. L. A. L. Abdussattar, “BIFORE or Hadamard Transform”, *IEEE Audio Electroacoust. Trans*, AU-19, pp. 225 – 234, 1971.

[2] Altera, *Digital Library of FPGAs*, San Jose, Jan. 2006, www.altera.com.

[3] S. F. Bocklisch and U. Priber, “A Parametric Fuzzy Classification Concept”, *Proceedings of the Int. Workshop on Fuzzy Sets Applications*, pp. 147-156, March 3-8, 1985, Eisenach, Akademie-Verlag, Berlin, Germany, 1986.

[4] S. Brown, “Latest Developments in On and Off-line Inspection of Bank-Notes during Production”, *Proceedings, IS&T/SPIE 16th Annual Symposium on Electronic Imaging*, Vol. 5310, pp. 46-51, San Jose, CA, USA, Jan. 2004.

[5] B. Jähne, *Digital Image Processing.* Springer, New York, 2002.

[6] V. Lohweg, C. Diederichs, “An Image-Processing-System-On-Chip Based on Nonlinear Generalized Circular Transforms and Fuzzy Pattern Classification”, *IEEE-EURASIP Workshop on Nonlinear Signal and Image Processing*, Grado-Trieste, Italy, June 2003.

[7] V. Lohweg, C. Diederichs, D. Müller, “Algorithms for Hardware-based Pattern Recognition”, *EURASIP Journal on Applied Signal Processing, Nonlinear Signal Processing and Image Processing - Part I,* Volume 2004, No.12, New York, Sept. 2004.

[8] T. Türke and V. Lohweg, “Real-Time Image-Processing-System-On-Chip For Security Feature Detection and Classification”, *Proceedings, IS&T/SPIE 16th Annual Symposium on Electronic Imaging*, Vol. 5297, pp. 204-211, San Jose, CA, USA, Jan. 2004.

[9] J. G. Schaede, “Bridging the Process Gaps In Finishing through Numbering and Inspection Evolution”, *10th International Currency Conference 2005*, 2-5 Oct. 2005, Montréal, Québec, Canada, 2005.

[10] H. Schulz-Mirbach, “Constructing invariant features by averaging techniques”, *International Conference on Pattern Recognition (ICPR)*, IAPR, Vol. 2, Jerusalem, Israel, pp.387-390, Sept. 1994.

[11] S. Siggelkow and H. Burkhardt, “Image Retrieval Based On Local Invariant Features”, *Proceedings of the IASTED International Conference Signal and Image Processing,* pp. 369-373, Las Vegas, Nevada, USA, Oct. 1998.