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LOCI FEATURES FOR BINARY PATTERN RECOGNITION

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ABSTRACT

We detail the concept of Loci features which provide a directional textural measure that can be interpreted as a count of the number of strokes in a given direction when applied to character recognition. Loci features, which are essentially extensions of early work by Glucksman, have been proposed for the recognition of Chinese characters. We report on the development of a classifier system based on loci features which has been applied experimentally to the classification of a sub-set applied of digitised Chinese fonts. and to binarised Brodatz textures.

I INTRODUCTION

Early template based character recognition (OCR) was to a significant degree font-specific, To overcome these limitations Glucksman [1] introduced an approach to character recognition based on counting the number of 'crossovers' background - foreground - background averaged over a set of traverses of a windowed character, these traverses being either horizontal or vertical. Roman characters include both strokes and loops, which are treated like pairs of strokes by this analysis. Serifs and font features may increase the crossover count. However, the feature of Roman character is their simplicity. Hence Glucksman's scheme has merit for roman characters and letters, where essentially it provides an (almost) font independent descriptors for characters. However, Chinese characters involve many strokes, primarily horizontal and vertical, and essentially have significant internal arrangement reflecting their composition from more 'atomic' ideographs. Nevertheless, several authors, notably Tsukumo [5], have generalised the definition of loci Feature, and applied it purposefully to the identification of both printed and handwritten Chinese Characters.

In this paper we first present in Section 2 the definitions of Loci Features, namely the four direction FD Loci features, the Outer Perimeter Loci feature, and the four corner Loci Feature.in Section 4 we present examples of their application to different Roman fonts, and to Chinese characters. We have used these four measures over a sub-set of digital Chinese fonts to compare classification against classification scheme previously introduced by You et al [2] related to the 4-corner scheme of Chinese lexiography.

As the FD measure is very much a texture measure, we have also applied it to binary textures which were actually thresholded Brodatz textures, in Section 4. We present our conclusions in Section 5.

2 FOCI FEATURES FOR CHARACTER RECOGNITION

Early optical character recognition involved the use of imaging slits at various angles to the character row so as to integrate the foreground in such directions. Such integration technique essentially assumes a constant width, and is easily confused by font variants. In a hard to obtain paper Glucksman[1] introduced loci .Features for roman character recognition. Glucksman's features, here call**ed** four direction foci features, are best indicated by an example given in the figure below:

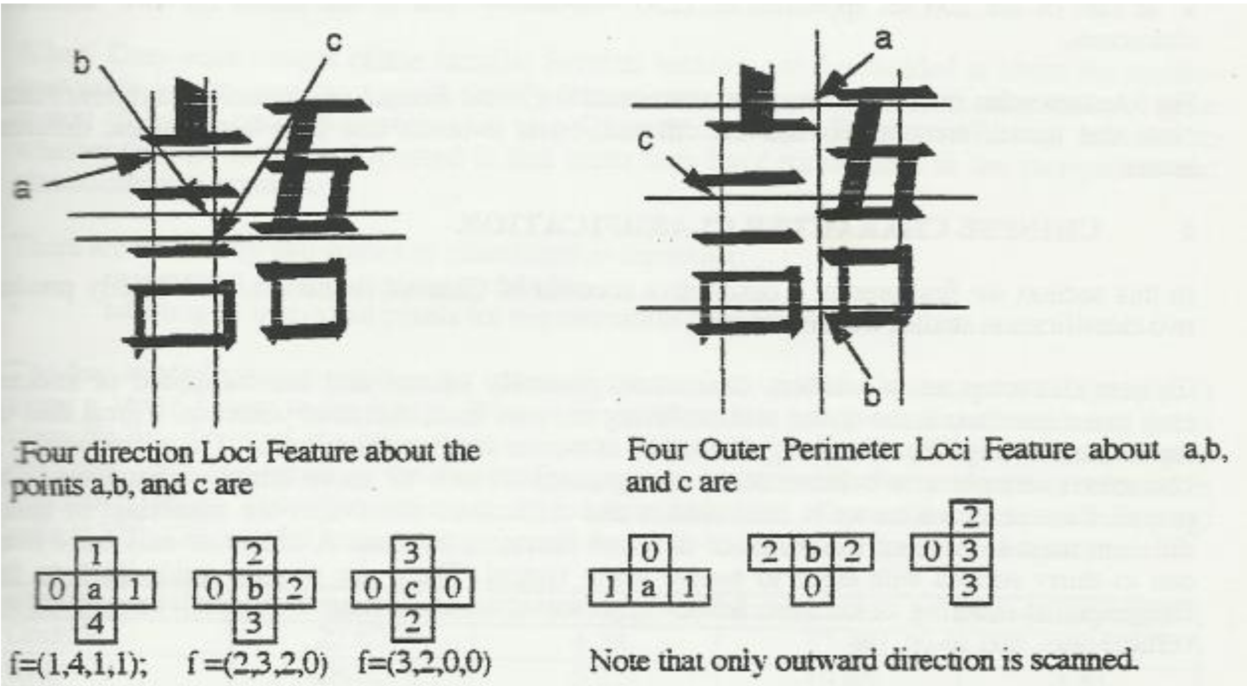

Fig 1 Loci Features

A verbal description of the computation of the four direction foci feature is as follows:
The binary pattern being studied is enclosed within a rectangular block, and local FD loci feature determined at each pixel of the block, as follows: From every background picture element of a binary pattern, scanning lines are followed in four directions, north, south, east and west, where the north direction is upwards on the screen. The scanning lines run from the pixel in question to the specified rectangular boundary of the character block. Along each such scanning line the number of "strobe crossings" background -foreground- background transitions is counted. The four local counts constitute the local FD loci Vector. The block frequency vector F is the histogram of the local vectors for each pixel in the block.

$$F[\ ] = \sum_{\text{pixels}} F[f] \text{ -1-+}$$

Note that

- The FD frequency feature is invariant under NS and EW translation of the character within the character block::

This means that in character recognition the character block does not need to be centred over the character position.

Character recognition in this context is carried by use of any convenient measure of difference between two frequency functions, In the C-Code used in this research the Manhattan distance was used per

```
for (k=0;  k<256; k++)
    freq_diff_table[i][j] += labs(freq_array[i][k] - freq_array[j][k];
```

k is one of the 256 set appearances, (256 = 4x4x4x4) and i,j are labels for two 'different' characters.

Fig 3A shows this difference measure determined for a few Roman characters of different fonts. Note that the differences between the different fonts is much less than between the different letters.

3 CHINESE CHARACTER CLASSIFICATION

In this section we first present a descriptive account of Chinese characters, then briefly present two classification studies we have made.

Chinese characters are of uniform dimension, generally square, and are composed of strokes. each one a line that can be drawn without lifting the pen. Each character possesses a great deal of structure. (See Fig 3B). Many regularities of stroke configuration occur. Quite frequently, a character is simply a two-dimensional arrangement of two or more simpler characters. The overall Chinese character set is rich: strokes and collections of strokes are combined in many different ways to produce thousands of different character patterns. A character may have from one to thirty strokes with eight to twelve being typical. There are general guide-lines to the calligraphical ordering of strokes: left-to-right, top-to-bottom, long horizontal strokes before vertical ones, and so-on. [51

The structure of a Chinese character may be specified hierarchically, with strokes considered as the basic picture element.. Nearly all strokes consist of one or a small number of straight-line segments which appear as either horizontal, vertical, or in a direction along one of the main diagonals. Strokes are combined to form units, called components, which occur in many different characters. Finally each character consists of a two-dimensional arrangement of one or more components. Usually, one component of a character gives a clue to its meaning and the rest gives a clue to its pronunciation.

Rankin and his associates [8) developed a two-level grammar for Chinese characters involving

- a "generative" grammar which generates characters by means of a list of components and a set of rules for component combination. Components are defined to be "often-recurring subparts"
- a "decomposition" grammar which explicates the process involved in the formation of components from strokes.
-

Rankin's work continues to be cited in the literature, but the writers do not know of recognition or classification that significantly builds on this theory,

In contrast, Roman characters comprise "strokes" that are joined to zero, one or even two loops. There is no internal structure. Thus the applicability of foci analysis to large sets of Chinese characters, such as the few thousand used by the Japanese, is not completely clear.

In this study our interest was in seeing the extent to which classification could be achieved using FD Foci.. Hence we restricted the study to digitised Chinese Characters sized 16x16 which were determined by reverse engineering a Chinese word processor package. Some recent work has been directed to the problem of feature distortion [61 Ten characters of the set are shown in Fig 3 B, where FD Loci Frequency differences are tabled. To simplify discussion we refers to these 10 characters as 1 ..10. The Table of Fig 3B shows such differences as (6,5) = 11785, while (4,1) = 30545. The measure does match naive viewers concept of similarity.

Could a thorough-going classification be readily achieved ?. We have implemented the ART1 classifier of Carpenter and Grossberg [5] have examined the capability of this system to produce clusters,.

4 BINARY TEXTURE ANALYSIS

When Gray-scale images of the familiar Brodatz textures are thresholded at about the middle-gray value, human viewers may still readily discriminate these textures. It is clear that any finite region of such a binary texture is akin to a Chinese character. Thus the question arises as to whether the foci methods discussed in this paper may have some merit in the recognition and classification of textures.

There are essentially two grades of classification capability:

- recognition of large regions eg 64x64
- labelling of individual pixels for segmentation purposes

The foci-related measure used is the count of the number of stroke crossings in a zigzag path along a 16x16 square in the image: Two such measures are used, one for the crossing count along the row direction, the other for the column direction. For the row/column count the path used runs from one corner to the diagonally opposite corner, with alternating rows/columns in opposite direction. These two quantities were determined about all possible 16x16 (overlapping) cells in 128x 128 samples texture samples, and the mean and standard deviation determined:

Brodatz Texture*	f(along rows)	stdv (along rows)	f(along cols)	stdv(along cols)
CorkD4	22.67	4.28	17.30	3.65
GrassD9	28.62	5.32	19.85	3.61
CalfD24	29.67	4.77	19.76	3.84
CanvD21	18.03	4.57	26.80	2.97
CanvD20	15.40	4.87	7.29	4.74
PaperDS7	20.98	4.06	19.83	3.45
PebblesD54	13.76	5.71	10.96	4.70
Pi2D94	20.16	4.55	17.14	3.85
RaftD84	18.62	4.28	16.59	3.67
SandD29	2a27	4.3n	16.39	3.68
StralvD15	27.31	6.61	10.86	4.24
WireD6	22.12	3.35	17.86	2.71

***** The textures were thresholded at gray-scale value of 128

5 CONCLUSIONS

Directional Loci which essentially count the number of strokes in a given direction are very easy to compute quantities. We have examined the application of the four directional FD Loci, using the frequency measure as a metric. Even restricting attention to 16x16 fonts, the range of character differences seems small, and quite unsuitable for distinguishing more than a few tens of Chinese fonts. However, using several such foci measures in conjunction looks to be a promising direction to take.

Using a simple foci-like measure to characterise textures,, gives for the textures examines a two measures that in most cases would discriminate well largish samples (64x64) of textures. However, the variance of the measure was high, and only limited segmentation is possible for images composed of these textures. However this is a very simple measure to compute as a measure of directional coarseness, and may be useful in image query systems.

6 REFERENCES

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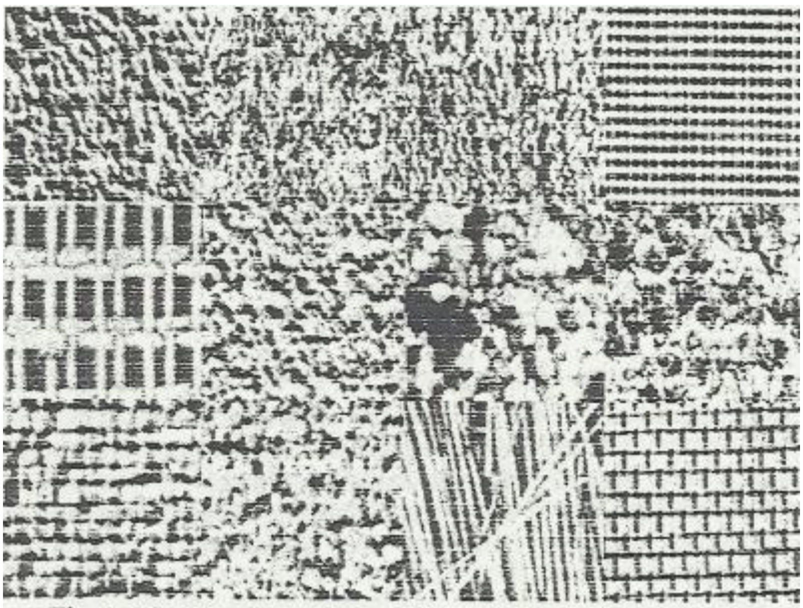

Fig 4 The Brodatz texture of the Study in Raster Order

	A	A	B	B	C	C
A	00000	14973	40916	36379	45292	42097
A	14973	00000	35195	32320	36523	34358
B	40916	35195	00000	9443	36122	33151
B	36379	32320	9443	00000	38529	35964
C	45292	36523	36122	38529	00000	8279
C	42097	34358	33151	35964	8279	00000

Fig 3: FD Loci Frequency difference for fonts
A Roman alphabet sub-set B Chinese font sub-set

	哄	咪	亭	亮	俟	俊	袄	祉	祈	祇
哄	00000	17170	28933	30545	28334	25825	26238	25127	20241	30351
咪	17170	00000	29213	27407	27888	25647	22876	24699	23947	30289
亭	28933	29213	00000	17094	23623	24558	26571	29460	26984	29908
亮	30545	27407	17094	00000	28527	26854	26669	32030	29714	30868
俟	28334	27888	23623	28527	00000	11785	23132	24969	24889	28085
俊	25825	25647	24558	26854	11785	00000	22701	24580	21952	27318
袄	26238	22876	26571	26669	23132	22701	00000	15317	15963	18509
祉	25127	24699	29460	32030	24969	24580	15317	00000	14470	27712
祈	20241	23947	26984	29714	24889	21952	15963	14470	00000	26402
祇	30351	30289	29908	30868	28085	27318	18509	27712	26402	00000