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6 TEXTURE CLASSIFICATION WITH CHANGE POINT STATISTICS

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ABSTRACT

Nonparametric techniques used to solve the change point problem are applied to the problem of texture classification. The texture classification problem is not formulated as a hypothesis testing problem, but instead our interest lies in the values of K_T, K_T^+, and K_T^-, the change point statistics.

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1. Introduction

Although the problem of texture classification has been thoroughly studied, it is still desirable to investigate whether or not we can model the random behavior of the imaging equipment and still achieve a reliable classification scheme. To this end, we introduce a statistical test previously used to determine whether or not a sequence of random variables has a change point.

<u>Definition</u>: A change point is defined to be an index τ in a sequence $x_1, x_2, \ldots, x_T$ of random variables such that $x_1, x_2, \ldots, x_\tau$ have a common distribution $F_1(x)$ and $x_{\tau+1}, \ldots, x_T$ have a common distribution $F_2(x)$, where $F_1(x) \neq F_2(x)$.

Note that there is no change point if $\tau = T$.

Determining whether or not a change point exists in a sequence of random variables is related to two texture classification methods described in Weszka et al. [1]. From the description of the change point statistics in Section 2, this association will become clearer.

2. Change point statistics

Many authors have presented approaches to solving the change point problem. These include tests for a change in mean level (Sen and Srivastava [2,6]), likelihood ratio tests (Hinkley [3]), Bayesian approaches to inference about τ (Smith [4]), and distribution-free approaches as in McGilchrist and Woodyer [5] or Sen and Srivastava [2].

We desire to use a method which makes no assumptions about the initial distribution. Thus we consider a version of the Mann-Whitney U statistic. This statistic can be used for testing the hypotheses of no change point versus change point at τ.

Let us now examine the Mann-Whitney statistic for testing if two samples ($x_1, x_2, \ldots x_t$ and $x_{t+1}, \ldots, x_T$) come from the same population. The statistic $U_{t,T}$ is defined as

$$U_{t,T} = \sum_{i=1}^{t} \sum_{j=i+1}^{T} D_{ij}$$

where

$$D_{ij} = \mathrm{sgn}(x_i - x_j)$$

To use the above statistic to solve the change point problem, and for our purposes, we let t vary such that $1 \le t < T$. Then we introduce the following statistics:

$$K_T = \max_{1 \le t < T} |U_{t,T}| \tag{3}$$

$$K_T^+ = \max_{1 \le t < T} U_{t,T} \tag{4}$$

$$K_T^- = -\min_{1 \le t < T} U_{t,T} \tag{5}$$

which are the definitions in Pettitt [7]. We refer to K_T, K_T^+, and K_T^- as the change point statistics. It is easy to see that

$$K_T = \max(K_T^+, K_T^-) \tag{6}$$

It is precisely this fact which we wish to investigate.

K_T^+ and K_T^- will be computed along the columns, rows, and diagonals of an image, and we wish to see whether K_T is K_T^+ or K_T^-. This gives an indication as to the nature of the changes in sign of gray levels between pixels in different portions of the image. Thus, if $K_T=K_T^+$, the majority of the changes are positive; if $K_T=K_T^-$, the majority of the changes in sign are negative.

3. The relationship between change point statistics and other features

In this section we wish to show the relationship between the change point statistics and other texture classification features alluded to in Section 1.

Weszka et al. [1] also form differences of gray levels, although these differences are absolute differences for a given displacement δ. The probability density of these differences is estimated by the number of occurrences, and various measures are computed from these probability estimates, P_δ. The change point statistics use the sign of the difference and thus include additional information relating to the signs of the changes in gray level. Also, the displacement is varied up to a given limit ($1 \leq t < T$) and so information is included over various displacement values, δ.

The survey by Haralick [8] as well as Weszka [1] discuss the use of run length statistics. This is simply counting the number of pixels with the same gray level. This, too, is included in the change point statistics, since the run length, t, is varied between 1 and an upper bound of T. Pixels of the same gray level in a run add 0 to the sum $U_{t,T}$ by definition of the sign function.

The gray-tone spatial dependence matrices of Haralick [8] and Haralick et al. [9] are used to model the probabilistic behavior of texture. What is not mentioned is the fact that there are underlying assumptions in using Pearson product moment correlation, and these statistics cannot be arbitrarily applied. Siegel [10] indicates that the Pearson product moment correlation requires scores in at least an equal interval scale, and that the scores be from a bivariate normal population. If we are dealing with gray levels, the first assumption is satisfied (that of equal scale), but the second assumption of normality may not be met.

Thus we have chosen to use distribution-free statistics where no assumptions other than continuity of $F(x)$ are made. This is even weaker than the normality assumption, since the continuity assumption is underlying the assumption of normality.

Here we have shown similarities and differences between change point statistics and previous methods for texture classification. The similarities indicate that we can expect similar results with change point statistics, yet the statistical differences indicate that a larger sample size is needed for the same level of significance. The reader is referred to Randles & Wolfe [11] for a discussion of asymptotic relative efficiency of distribution-free statistics.

4. <u>The computation of change point statistics</u>

Recall that in order to compute K_T, K_T^+, and K_T^-, it is necessary to compute

$$U_{t,T} = \sum_{i=1}^{t} \sum_{j=t+1}^{T} D_{ij} \tag{1}$$

for values of t such that $1 \le t < T$, where T is fixed. In the results presented here, several values of T were used only to see if there existed a value T beyond which the results did not vary. In this work both t and T represented positions within an image.

The above formula can be computationally expensive. Empirical results show that for values of $T \ge 10$, computation can exceed 10 minutes. As Haralick et al. [9] indicate, it is desirable to use a method that is computationally feasible. We present an alternative to equation (1) that is briefly mentioned in Pettitt [7], but is not fully discussed.

In equation (1), note that

$$U_{t,T} = \sum_{i=1}^{t-1} \sum_{j=t+1}^{T} D_{ij} + \sum_{j=t+1}^{T} D_{tj} \tag{7}$$

Now

$$\sum_{i=1}^{t-1} \sum_{j=t+1}^{T} D_{ij} = \sum_{i=1}^{t-1} \sum_{j=t}^{T} D_{ij} - \sum_{i=1}^{t-1} D_{it} \tag{8}$$

Substituting (8) into (7):

$$U_{t,T} = \sum_{i=1}^{t-1} \sum_{j=t+1}^{T} D_{ij} + \sum_{j=t+1}^{T} D_{tj} \tag{7}$$

$$U_{t,T} = \sum_{i=1}^{t-1} \sum_{j=t}^{T} D_{ij} - \sum_{i=1}^{t-1} D_{it} + \sum_{j=t+1}^{T} D_{tj} \tag{9}$$

Notice that $U_{t-1,T} = \sum_{i=1}^{t-1} \sum_{j=t}^{T} D_{ij}$ by definition,

$$U_{t,T} = U_{t-1,T} - \sum_{i=1}^{t-1} D_{it} + \sum_{j=t+1}^{T} D_{tj} \tag{10}$$

Since $-\sum_{i=1}^{t-1} D_{it} = \sum_{i=1}^{t-1} D_{ti}$ by symmetry of the sign function

$$U_{t,T} = U_{t-1,T} + \sum_{i=1}^{t-1} D_{ti} + \sum_{j=t+1}^{T} D_{tj} \tag{11}$$

Also since $D_{tt}=0$ by definition, we arrive at our final recursion formula

$$U_{t,T} = U_{t-1,T} + \sum_{i=1}^{T} D_{tj} \tag{12}$$

Hence our computation can be speeded up by storing the previous values of $U_{t-1,T}$ for the computation of $U_{t,T}$. The empirical results indicate that using this formula allowed us to compute $U_{t,T}$ for up to T=20 in under two minutes.

Be careful to note that the above equations still only deal with one dimensional random variables. In order to apply these statistics to images, it is necessary to make a two-dimensional adjustment. We have done this in the following manner:

When computing $U_{t,T}$ along the rows (direction "I") let

$$D_{ij}^{I} = \sum_{k=1}^{n} \mathrm{sgn}(x_{ik} - x_{jk}) \tag{13}$$

where n is the number of rows. When computing $U_{t,T}$ along the columns (direction "J"), we use a similar equation

$$D_{ij}^{J} = \sum_{k=1}^{n} \mathrm{sgn}(x_{ki} - x_{kj}) \tag{14}$$

A slightly different equation is used to compute D_{ij} along the image diagonals. We desire to capture information from the diagonals throughout the image, not the longest diagonals only. This is accomplished by varying the slope of the diagonal. We arrive at

$$D_{ij}^{K} = \sum_{k=1}^{n} \mathrm{sgn}(x_{ki} - x_{(n+1-k)j}) \tag{15}$$

where K denotes the diagonal axis. One can easily see that the differencing takes place along a line whose slope is varied, and D_{ij}^{K} is the sum of such differences.

By computing D_{ij}^{I}, D_{ij}^{J}, and D_{ij}^{K}, we will have $U_{t,T}^{I}$, $U_{t,T}^{J}$, and $U_{t,T}^{K}$. With these U statistics in hand, we can compute K_T^{+}, K_T^{-} and eventually $K_T = \max(K_T^{+}, K_T^{-})$ for each of the directions I,J, and K. The triple $(K_T^{I}, K_T^{J}, K_T^{K})$ is used to characterize a given image.

In practice, instead of using the values of the K_T, we use instead the sign (+/-) of the change point statistic (K_T^{+} or K_T^{-}) that K^T equals. Thus for each sample we have a triple of directions indicated by signs. Intuitively, these signs indicate whether the gray levels increase or decrease in value in the specified directions. If a sign is positive (negative), this means the difference in gray level is positive (negative), and the gray level has increased (decreased) in value. The following sections describe some results of using change point statistics in practice.

5. Experimental results

This experiment consisted of two parts: First, we want to see if change point statistics can be used in texture classification, and secondly we are interested in determining if it is necessary to let T approach the value of n for an n×n image. This is motivated by the fact that the computation of $U_{t,T}$ is so costly, and if T=n, we have a combinatorial explosion.

The results are presented in the following format: For each of the directions I,J, and K we compute K_T^+ and K_T^- by equations (4) and (5). With K_T^+ and K_T^- we compute K_T by equation (6). For each sample and axis, we record either + or - depending on whether $K_T=K_T^+$ or K_T^-, respectively. Thus for each sample we have the triple of change point statistics (values of K_T) represented by + or -. These are what we use to differentiate the texture samples.

For the second part of the experiment, we let T=5,10, and 20. The purpose of this is twofold: We desire to see if the computation can be completed and then we use these results as the training sets for classification. The classification results for the different values of T are compared to see if the classifications are the same.

The results are tabulated in Figures 1,2, and 3 for T=5,10, and 20, respectively. In this work, we have used texture samples of Mississippian Limestone and Shale(ML), Pennsylvanian Sandstone and Shale(PS), and Lower Pennsylvanian Shale(LP). Ten samples of each texture were used.

A texture classification decision rule similar to that of Haralick et al. [9] can be employed here. For each of the three groups (ML,PS,LP) we classify samples of that group by the most likely triple that occurs. For example, if a change point triple is +++ or --- ("flat") it is most likely to be PS(see Figure 2).

Again, looking at Figure 2, the majority of the ML samples have a - for the I axis whereas the LP samples have a + for the I axis. Therefore, if a sample does not exhibit flat structure as defined above, we classify it as ML or LP depending on the I axis statistic.

To test this decision rule, 10 samples were chosen randomly from among the ML,PS, and LP windows. Their change point statistics were computed, and they were classified accordingly. Their actual types are also given in Figure 4.

The second part of this experiment was to determine the accuracy of using a small value of T. Each of the training sets were used to classify the samples and the differences were examined. It is important to note that a preallotted amount of time was given to compute the training set statistics. This was done to see if the statistics could be computed in a reasonable amount of time.

6. Conclusion

In this paper we have presented a new method for texture classification. It has been shown that the use of change point statistics is very similar to other information previously used in texture classification, yet change point statistics maintain the distinct advantage of using distribution-free statistics. That is to say, our model of image and noise does not assume any form of the noise distribution. The probability distribution of the change point statistics themselves is independent of the probability distribution of the underlying random variable.

Figures 1,2, and 3 show the change point statistics for the training sets. Since for T=20, the computation did not finish, we conclude that this computation is prohibitive, even when we use the recursion equation and store intermediate results. We still wish to investigate whether or not the classifier is accurate in going from T=5 to T=10.

We see from Figure 4 that the classifier using change point statistics is about 90% accurate for the samples given. This is not entirely conclusive since it is still desirable to classify with the T=20 training set. Clearly, one future direction is to derive an algorithm even faster than equation(12) and a better search of the $U_{t,T}$ space for K_T^+ and K_T^-. Also, one could extend this work by training on a larger number of texture types. We have shown that change point statistics are valuable as an aid in texture classification.

	I	J	K		I	J	K		I	J	K
LP1	-	-	-	ML1	-	+	-	PS1	+	-	+
LP2	-	+	-	ML2	-	-	-	PS2	+	-	+
LP3	-	+	+	ML3	+	+	+	PS3	+	+	+
LP4	-	-	+	ML4	+	+	+	PS4	+	-	+
LP5	+	-	+	ML5	+	+	+	PS5	+	+	+
LP6	+	-	+	ML6	+	+	+	PS6	+	-	+
LP7	-	+	-	ML7	-	+	-	PS7	+	-	+
LP8	-	+	-	ML8	-	-	-	PS8	+	+	+
LP9	+	-	+	ML9	+	+	+	PS9	+	+	+
LP10	+	+	+	ML10	+	+	+	PS10	-	-	-

Figure 1. Change point statistics for T=5.

	I	J	K		I	J	K		I	J	K
LP1	+	-	+	ML1	-	+	-	PS1	+	-	+
LP2	+	+	+	ML2	-	-	-	PS2	+	-	-
LP3	-	+	-	ML3	-	-	-	PS3	+	+	+
LP4	-	+	+	ML4	+	+	+	PS4	-	-	-
LP5	-	-	+	ML5	-	+	-	PS5	-	+	+
LP6	-	+	+	ML6	-	-	-	PS6	+	-	+
LP7	-	+	-	ML7	-	-	-	PS7	+	-	+
LP8	-	-	-	ML8	+	+	+	PS8	+	+	+
LP9	-	-	+	ML9	-	-	-	PS9	+	+	+
LP10	-	-	-	ML10	+	+	+	PS10	-	-	-

Figure 2. Change point statistics for T=10.

	I	J	K
LP1	-	-	-
LP2	+	+	+
LP3	-	+	-
LP4	-	+	-
LP5	+	+	+
LP6	+	+	+
LP7	-	+	-
LP8	-	-	-

Figure 3. Change point statistics for T=20.

	I	J	K	Classification(T=5)	Classification(T=10)	Real Type
X1	-	+	+	LP	LP	LP
X2	-	+	-	LP	LP	LP
X3	+	-	+	PS	PS	PS
X4	-	-	-	ML	ML	ML
X5	+	-	+	PS	PS	PS
X6	-	-	-	ML	ML	ML
X7	+	-	+	PS	PS	LP
X8	+	+	-	PS	PS	PS
X9	+	+	-	PS	PS	PS
X10	+	+	+	ML	ML	ML

Figure 4. Change point statistics and classification of unknown samples.

References

1. Weszka, J. S., C. R. Dyer, and A. Rosenfeld, "A comparative study of texture measures for terrain classification," IEEE Trans. SMC, vol. SMC-6, 1976, pp. 269-285.

2. Sen, A. and M. S. Srivastava, "On tests for detecting changes in mean," Annals. of Statistics, vol. 3, 1975, pp. 78-108.

3. Hinkley, D. V., "Inference about the change point in a sequence of random variables," Biometrika, vol. 57, 1970, pp. 1-17.

4. Smith, A. F. M., "A Bayesian approach to inference about a change point in a sequence of random variables," Biometrika, vol. 62, 1975,, pp. 407-416.

5. McGilchrist, C. A., and K. D. Woodyer, "Note on a distribution-free CUSUM technique," Technometrics, vol. 17, 1975, pp. 321-325.

6. Sen, A. and M. S. Srivastava, "Some one-sided tests for change in level," Technometrics, vol. 17, 1975, pp. 61-64.

7. Pettitt, A. N., "A non-parametric approach to the change point problem," Applied Statistics, vol. 28, pp. 126-135.

8. Haralick, R. M., "Statistical and structural approaches to texture," Proc. IEEE, vol. 67, 1979, pp. 786-804.

9. Haralick, R. M., K. Shanmugam, and I. Dinstein, "Textural features for image classification," IEEE Trans. SMC, vol. SMC-3, 1973, pp. 610-621.

10. Siegel, S., Nonparametric Statistics for the Behavioral Sciences, McGraw Hill, New York, 1956, pp. 202-213.

11. Randles, R. H. and D. A. Wolfe, Introduction to the Theory of Nonparametric Statistics, John Wiley and Sons, New York, 1979.

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