A Feature Points Matching Algorithm Based on Wavelet Analysis

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ABSTRACT: *In this paper, we present an application of wavelet analysis on feature points matching. Wavelet coefficients which produced by wavelet transform can best display part character of the image. Through the new feature description and feature matching method, we can build a feature point database for each image and improve the efficiency of feature points matching. The experimental results show that this method is practicability, feasibility, good precision and fast speed.*

Categories and Subject Descriptors:
G.1.2 [Approximation]: Wavelets and fractals; **I.4.7 [Image Feature Measurement]**

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Computer Vision, Wavelet Transformation

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1. Introduction

Image matching is a fundamental aspect of many problems in computer vision. Most image matching methods can be divided into three main stages [1]: interest point detection, feature description and feature matching. The development of image matching by using a set of local interest points can be traced back to the work of Moravec on stereo matching using a corner detector [2], and the Moravec corner detector was improved by Harris and Stephens [3]. The Harris corner detector is very sensitive to changes in image scale, so it does not provide a good basis for matching images of different sizes. Lowe extended these ideas to scale invariance by maximizing the output of difference-of-Gaussian (DOG) detector in scale-space [4]. The scale invariant feature transform (SIFT) descriptor was proved to have the best performances among different types of image feature descriptors [5].

At any particular level $j+1$, we have the following relationship $V_j \oplus W_j = V_{j+1}$, Where W_j is a space orthogonal to V_j and $V_j \cap W_j = \{0\}$. The wavelet $\phi(x)$ and its integer translations form a basis for V_0. The wavelet $\psi(x)$ and its integer translates span W_0. These spaces decompose the function into its smooth and detail parts.

Scaling equation and Scaling function, wavelet function, decomposition and reconstruction algorithm are important factors of the multiresolution analysis. In this paper, we use Daubechies Wavelet analysis the image which is widely used in Multiresolution analysis.

For matching the image features, it was a common practice to use a histogram matching strategy called bin-by-bin measure [6]. The problem of identifying an appropriate and consistent scale for feature detection has been studied in depth by Lindeberg [7]. Wavelet transform has been used for obtaining multiresolutions at each frequency level in image matching [8, 9].

In this paper, we propose a new feature description and feature matching algorithm based on wavelet coefficients. Our algorithm has pay attention to reducing the amount of calculation and enhancing the matching effect for different images. The remainder of this paper is organized as follows: Section 2 briefly presents wavelet theory. Section 3 and 4 describe the proposed method in detail. Section 5 provides the experimental results and the analysis. Finally, there are conclusion and references.

2. Wavelet Theory

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. We now provide a basic introduction to the ideas of wavelet multiresolution theory [10]. For any function $f \in L^2(R)$ and a starting resolution level j_0, representation in the wavelet basis is given by

$$f(x) = \sum_{j_0,k} \alpha_{j_0,k} \phi_{j_0,k}(x) + \sum_{j_0,k} \beta_{j,k} \psi_{j,k}(x)$$
$$\phi_{j_0,k}(x) = 2^{j_0/2} \phi(2^{j_0} x - k) \qquad (1)$$
$$\psi_{j,k}(x) = 2^{j/2} \psi(2^j x - k)$$

The scaling function $\phi(x)$ and wavelet function $\psi(x)$ should be defined by the Equation 2. The key idea behind multiresolution theory is a sequence of nested subspaces$\{V_j, j \in Z\}$ such that

$$\text{(a) } V_j \subset V_{j+1}; \quad \text{(b) } \overline{\cup V_j} = L^2(\mathrm{R}); \quad \text{(c) } \cap V_j = \{0\} \qquad (2)$$
$$\text{(d) } f(x) \in V_j \; f(2^{-j}x) \in V_0;$$

Similarly, we can do the same work to other images, and then, all these statistics of different images will be recorded in a table shown in table 1.We row an order and give a serial number for each image in the table, and still store the image's name through ImageID.

In these statistics, we can see the fourth statistic (Minimum) always be 1, so its value is not high. Other statistics vary significantly, especially Mean, Median, Mode, Maximum and Range. As can be seen from the table that these statistics can fully express the characteristics of the image and we can call the table as the Image Feature Table (IFT).

3. The New Fearure Description

We proposed a new feature description based on wavelet coefficient. Wavelet coefficients statistics include Mean, Median, Mode, Maximum, Minimum, Range, Standard deviation, Median absolute deviation, Mean absolute deviation. We create a table using these wavelet coefficients statistics which are corresponded with the image. For example, we can use db-3 wavelet and the level is set as 2 for the implementation of a wavelet analysis to an image named 9-42. The statistic results are shown in Figure 1.

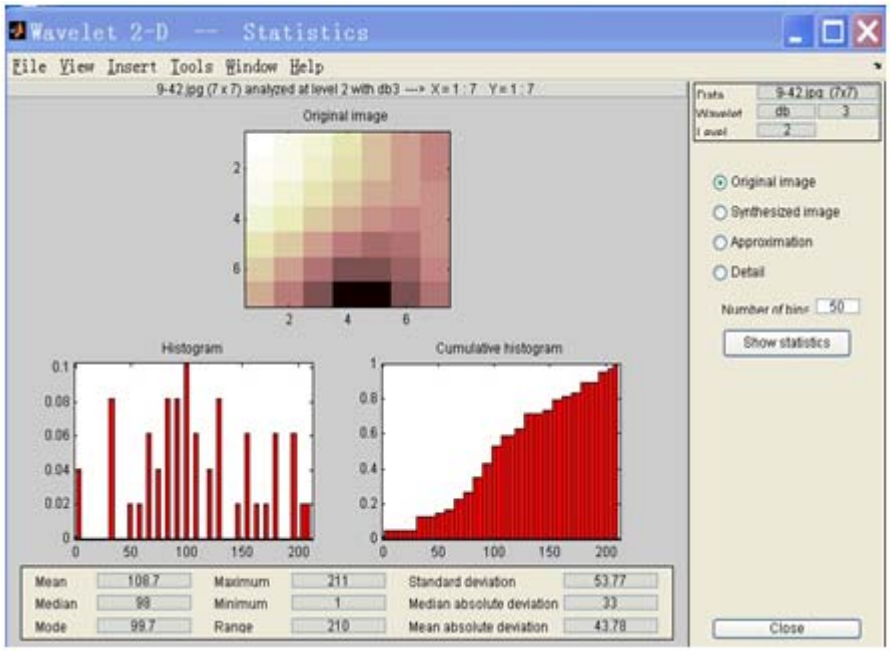

Figure 1. Wavelet Statistics of Image 9-42

4. The Proposed Method

For feature points matching, we use the Wavelet coefficients statistics as the points feature description for every image and we proposed a new matching algorithm according with this new points feature description.

In our method, first we use the traditional Harris detector and take a small picture to expand the scope of each point. The size of the small picture for each interest point may be 7×7 or 9×9, its center is the interest point (shown in Figure 2).

NO	ImageID	Mean	Median	Mode	Max	Min	Range	SD	MdAD	MnAD
1	9-42	108.7	98	99.7	211	1	210	53.77	33	43.78
2	30-165	52.65	51	18.03	132	1	131	35.41	31	29.62
3	34-171	74.22	82	91.75	122	1	121	28.6	10	22.04

SD = Standard Deviation, MdAD = Median Absolute Deviation, MnAD =Mean Absolute Deviation

Table1. Feature Description Table for Images

(a) Original Image (b) Detecting Interest Points (c) Small Pictures

Figure 2. Interest Points and Small Pictures

Second, establish the interest corners feature table through their corresponding small pictures just as Image Feature Table (shown in table 1) for each image. The number of the interest points in one image is always great. In the table 1, we only List the top ten. After this step each image will get an IFT table to characterize the features of its interest points. Third, we define a matrix D_I or the small picture I:

$$D_I = \begin{pmatrix} d_{I1}^1 & d_{I2}^1 & \cdots & d_{IK}^1 \cdots \\ d_{I1}^2 & d_{I2}^2 & \cdots & d_{IK}^2 \cdots \\ \vdots & \vdots & & \vdots \\ d_{I1}^m & d_{I2}^m & \cdots & d_{IK}^m \cdots \end{pmatrix}, (I, K \in Z^+, I \neq K)$$

$$d_{IK} = \begin{pmatrix} d_{IK}^1 \\ d_{IK}^2 \\ \vdots \\ d_{IK}^m \end{pmatrix}, d_{IK}^i = \left| M_I^i - M_K^i \right|, \ i = 1, 2, \cdots, m \quad (3)$$

The matrix D_I is used to calculate the statistics difference between each small picture. In the matrix D_I, I is used to identify a small picture that want to being matched with other small picture, and $1, 2, \ldots K$ are the identifiers for them. It should be noted that the pictureand the small picturesbelonging to the different images. Here is the further definition: each column of the matrix D_I is defined as the vector d_{IK}. Each component of the vector d_{IK} means the absolute value of the difference of each feature statistic between the small picture I and K, for example, if M_I^1 means the first feature statistic (Mean) of the small picture I and M_I^2 means the second feature statistic (Median) of the small picture I, so we can calculate $d_{IK}^1 = |Mean_I - Mean_K|$, $d_{IK}^2 = |Median_I - Median_K|$ and so on. At last, we comparison each row of the matrix D_I, and build a comparison vector S_I:

$$S_I = (S_I^1, S_I^2, \ldots, S_I^m), \ S_I^i \in \{1, 2, \ldots, K, \ldots\}, i = 1, 2, \ldots, m \quad (4)$$

We get the vector S_I through taking the minimum of each row of D_I, and if $d_{IK}^i = \min\{d_{I1}^i, d_{I2}^i, \ldots, d_{IK}^i, \ldots\}$, we then set $S_I^i{}_i = K$ which means that the small picture K (compared with the other small pictures) has the minimum difference of the feature statistic M^i for the picture I. Vector S_I is the matching criteria for our matching algorithm. Through vector S_I we can judge which one is the best match for picture I by calculating the probability of each component (S_I^i) in vector S_I (marked as $\rho_{S_{I_i}}$). If $0.875 \leq \rho_{S_{I_i}} \leq 1$ we call picture I and S_I are exact match, if $0.625 \leq \rho_{S_{I_i}} \leq 0.875$ we call the two pictures are approximate match, if $0 \leq \rho_{I_i} \leq 0.625$, then they can not match. For example, if for the small picture I, we get $S_I = (5, 5, 5, 5, 3, 5, 9, 5)^T$, we can calculate the probability of 5 as $0.625 \leq \rho_5 = 6/8 = 0.75 \leq 0.875$, similarly, we can also calculate $\rho_3 = \rho_9 = 1/8 = 0.125$. The result is that picture I and 5 are approximate matched, picture I and 3 or 9 can not being matched. Through this method we can calculate which picture has the smallest difference for which statistics, and considerate of all statistics we can judge whether this picture's interest points can be matched with interest point I.The same process can be recycled for every other small picture in the same image, because all the small pictures are according with the interest points, so through this matching process all the interest points can find their matching points in other images.

5. Experimental Results

We use the traditional Harris detector to detecting interest points and use Matlab wavelet toolbox for wavelet analysis. We build the Image Feature Table (IFT) for every image and the small interest pictures database for different images. Chose two images named P-1 and P-2 (shown in Figure 3), each of them has its IFT (shown in Table 2), only list the top ten too, and use our method for the feature points matching. The experimental results are shown in Figure 3. The other experimental results are shown in Figure 4.

6. Conclusion

In this paper, we proposed a new method based on the

ImageP-1 **ImageP-2**

Points Matching Results

Figure 3. Two Images and The Experimental Results

N0	ImageID	Mean	Median	Mode	Max	Min	Range	SD	MdAD	MnAD
1	9-42	108.7	98	99.7	211	1	210	53.77	33	43.78
2	30-165	52.65	51	18.03	132	1	131	35.41	31	29.62
3	34-171	74.22	82	91.75	122	1	121	28.6	10	22.04
4	35-199	70.27	66	108.9	131	1	130	38.41	33	33.01
5	35-206	84.73	98	121	130	1	129	39.58	32	34.59
6	37-162	79.8	76	67.81	132	1	131	28.17	9	21
7	38-140	129.1	157	164.5	208	1	207	68.45	41	59.48
8	38-153	104.3	106	3.04	205	1	204	66.66	29	58.14
9	40-174	54.59	48	47.62	127	1	126	31.96	16	26.42
10	40-201	77.55	100	100	133	1	132	41.88	22	36.47

SD = Standard Deviation, MdAD = Median Absolute Deviation, MnAD =Mean Absolute Deviation

Table 2. Feature Description Table for Image P-1 and Image P-2

Figure 4. The Experimental Results

weighted statistics of wavelet coefficients for feature points matching and we can build a feature point database for each image which is used for feature points matching. Feature point database stores the wavelet coefficients according with the interest points in the image. Through wavelet analysis method, the critical information of an image can be stored in the image feature database. The proposed matching algorithm can improve the efficiency of feature points matching through calculating difference matrixD_I. The experimental results show that this algorithm is quite robust and reliable for feature points matching and can match several pictures at the same time.

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