K-Local Cross Correlations Mechanism for Image Matching in Sequential Digital Images

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المستخلص

بالنسبة للصور المتتابعة، يتم تقديم آلية جديدة لمطابقة الصورة لغرض تحديد الاختلافات المقابلة بدلا من مطابقة الصور بالكامل. النموذج المقترح هو شكل محدث من نموذج الارتباط المتبادل القياسي الذي يكشف شدة الاختلافات للمواقع المقابلة على الصورة بأكملها معا. في نموذج الارتباط المتبادل القياسي، المستويات عالية الشدة في المناطق المضاءة تؤثر على مستويات منخفضة الشدة في المناطق المظلمة، والعكس بالعكس. الشكل المقترح يقسم الصورة إلى مناطق محددة، ويقيس الارتباط بين هذه المناطق. الشكل المحدث من العلاقة الترابطية يأخذ بنظر الاعتبار الاختلافات في المجالات ذات الصلة، التي توفر فروقا محددة بين المجالات ذات الصلة. هذه الفروق هي أكثر موثوقية من حساب الاختلافات بين المجالات غير المتصلة كما هو الحال في الشكل التقليدي للارتباط المتبادل. الشكل المحسن من الارتباط المتبادل قدم معلومات أكثر دقة حول الصور ذات الصلة.

Abstract

For sequential images, a new image matching mechanism is introduced for the purpose of locating corresponding differences instead of matching entire images. The proposed form is an adaptive form of standard cross-correlation form which detects intensity differences for the corresponding locations over the whole image together. In the standard form of Cross-Correlation, high levels of intensities in lighted areas may affect low levels of intensities in dark areas, and vice versa. The proposed form divides the image into number of blocks, and measures the correlations of the corresponding blocks. In such form, adaptive cross correlation considers the differences in the related areas, which provides specified differences between related areas. Such differences are more reliable than computing differences between un-related areas as in traditional form of cross correlation. Enhanced form of cross correlation provided more accurate information about related images.

Introduction

Similarity and differences between two images is highly recommended in many applications like image matching, feature detection, motion detection and Region of Interest (ROI). It also can be used in the detection of sophisticated components over the image. On the other hand, the correlation between two signals (cross correlation) is a standard approach to feature detection [1]. As well as an efficient and effective measure of the distance (dissimilarity) between histograms plays an important role in evaluating the relation between two images [2]. This relation between images is highly demanded spatially [1]. Cross correlation can also provide an imagination about the distances between two types of features in order to produce a new predicted feature [3]. In the previous types of usage for cross correlation, the distances are computed between the corresponding locations of the entire image, and for the accumulated results, each value has two types of effects on its difference from the its corresponding value. First one is the pure difference from the corresponding value, and the effects of the far values in the other places of the image. In other words, similar areas are affected by the distances of different corresponding areas in other parts of the image. Although cross correlation is essentially used for comparing two signals and evaluate their closeness [4], literatures proposed different approaches to utilize the methodology of such statistical comparison. Cross correlation was applied on Haralick's Texture to propose a new set of features that can be used in image classification [5]. This paper proposes a new form of cross correlation which handles such problem.

Sequential Images

In such type of digital images, some areas have fixed details, while others are changeable, see Fig 1. Medical images (MRI, Fluoroscopy... etc.) and image sequence in video files are common types of sequence images. Overall measures of changes, in such image type, have total view in performed calculations for the whole image, in other words, they may not distinguish between fixed and changed areas. To overcome such obstacle, such measuring techniques should apply more focus on inner changes in successive images, which are more important in some issues.

Cross Correlation:

Cross correlation (CC) is a statistical measure, which is essentially used for measuring the relation between close images [6]. It is widely used by many literatures in sequential images and motion detection applications [7]. The main role of CC, in such applications, is to measure relation between two variables,

(a): fluoroscopy (b): fluoroscopy (c:) fluoroscopy

Figure 1: Samples of sequential images

each of which represents pixel values of the related image. CC values vary from (1) to (-1). According to Eq. 1, the sign of CC depends on the sign of difference between pixel values and their average. If CC value is near (+1), then the two images are highly related. If the value is near to (0), then the correlation between the images is weak. Negative value of CC indicates the dissimilarity between the two images [6].

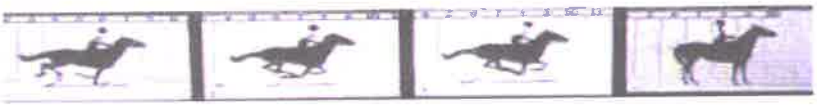
$$CC = \frac{\sum\sum(x_i-\mu_x)(y_i-\mu_y)}{\sqrt{\sum\sum(x_i-\mu_x)^2(y_i-\mu_y)^2}} \ldots\ldots\ldots\ldots\ldots (1)$$

Where:

x_i, y_i: Pixel values from related images

μ_x, μ_y: the average of pixel values in each image.

Depending on the average value of image pixel values measures the relation between studied pixel and the all remaining pixels, while some of them have no changes over the whole sequence of images, see Fig 1. Considering non-variant pixels provides high value for CC since they are the same in all images, see table 1. By analysing Fig 2, it can be visually detected that images (b and c) are closer to each other than other images, and (a) is closer to them than (d). Consistently, CC values in Table 1 explain correlation levels between



(a) (b) (c) (d)

Figure 2: sequential images that contain some variant parts

the images in Fig 1, yet the lowest value among them is (0.814) which is still relatively high. Background values and most of horse and rider pixel are still the same providing high value for CC. On the other hand, changing pixels such as horse legs and tail in addition to rider position have low level of effect on the final CC value.

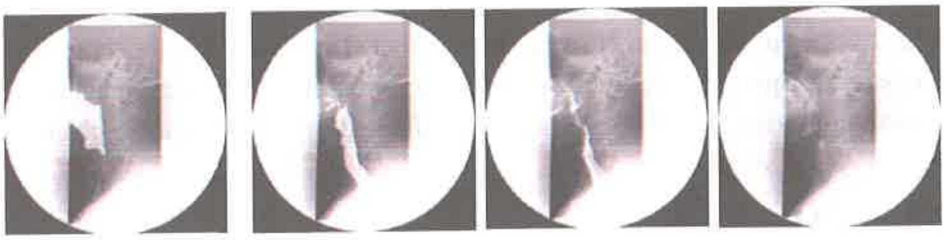
Table 1: CC values for images in Fig 2

	a	b	c	d
a	1	0.862	0.871	0.911
b	0.862	1	0.967	0.814
c	0.781	0.967	1	0.859
d	0.911	0.814	0.859	1

Due to its sensitivity in the huge amount of numbers, average measure provides similar values for different images with high number of pixels [10]. Accordingly, CC provides less sensitivity to changes detection in related images with fixed details, which is also noticed in sequential medical images, see Fig 3. In such images, motion detection is important, and partial changes are much more significant than fixed detail; medical diagnose depends on shape, size and changed location of the moved white areas, and ignore other details such as black square, white circle and some fixed details inside the middle rectangular [8]. Standard CC considers all image pixels and provides high CC values even for medically different images, see table 2.

Table 2: CC values for images in Fig 3

	a	b	c	d
a	1	0.8630	0.8603	0.7971
b	0.8630	1	0.8991	0.8058
c	0.8603	0.8991	1	0.9426
d	0.7971	0.8058	0.9426	1



(a) (b) (c) (d)

Figure 3: Fluoroscopy sequential images that depends on motion detection

K-Local Cross Correlations (KLCC)

Considering CC in corresponding local areas provides more detailed information about corresponding parts of the image. Dividing studied images into corresponding inner blocks provides number (K) of local sets, and each of them provides independent local CC. As a result, for each image, K-Local Cross Correlations (KLCC) will be computed. Two types of measures are obtained in this approach. In the first one, each block provides local measure about the relation between their corresponding blocks, whereas in the second one, the average of local CC's is used to represent cross correlation of the whole image. In order to compute KLCC, CC (Equation 1) is modified into the adaptive form that computes local CC between each corresponding block and the general KLCC, which is the overall view of the correlation between the two images:

$$KLCC_{i,j} = \frac{\sum_{h=1}^{32}\sum_{k=1}^{32}\left(x_{32(i-1)+h} - \mu_x\right)\left(y_{32(j-1)+k} - \mu_y\right)}{\sqrt{\sum\sum\left(x_{32(i-1)+h} - \mu_x\right)^2 \sum\sum\left(y_{32(j-1)+k} - \mu_y\right)^2}}$$

$$KLCC = \frac{\sum_{i=1}^{8}\sum_{j=1}^{8} KLCC_{i,j}}{8 \times 8}$$

Where:

x: pixel value
μ: average of pixel values
i, j: indicators for image blocks
h, k: indicators for pixels within each blocks

KLCC determines the effects of the average of each local CC within the values inside the specific block; in other words, computed average considers only pixel values of the specific block without considering pixel values of different areas. Accordingly, local CC of fixed area is not affected by pixel values of changing areas, and vice versa.

Results and Discussion

To discuss the results, proposed methodology utilised a standard dataset of (150) sequential medical images and a collected dataset of (98) sequential images. Compared images are divided into (64) blocks, i.e. 8 rows and 8 columns; each block contains (32×32) pixels, see Fig 4. Computing KLCC between corresponding blocks provides detailed information that describe the relation between the two images, such information determine which parts of the image has more changes, see Table 3. In this table, two types of changes are detected; first one is insignificant changes, which can be occurred because of imaging errors [9].Second type of changes detects significant changes which are caused by component motion within the same image. Such type of changes can be detected in (3,3), (4,3), (4,4), (5,3), (5,4), (6,4) and (7,4) blocks; in these blocks, white area moves across image blocks causing significant changes in pixel values. Some of KLCC values are negative indicating that pixel values are smaller than their average. For the optimal case, in which two images are totally related and pixel values are still the same, the correlation value will be (1).

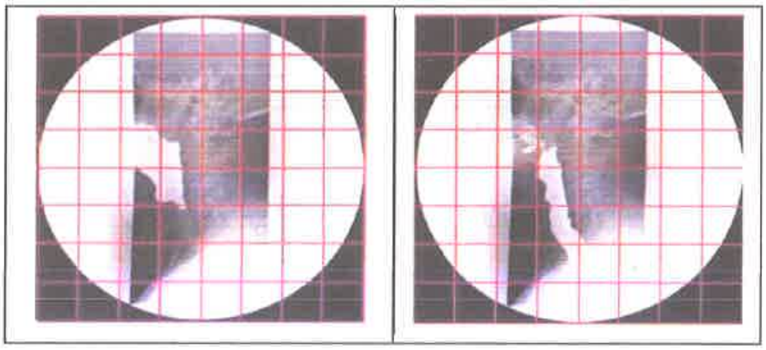


Figure 4: dividing the images into number of corresponding blocks

By measuring the distance between the real and optimal correlation value, changes within image blocks can be detected. Fig.5 indicates changes over corresponding blocks, and the detected blocks with potential motion.

Table 3: KLCC values for images in Fig 4

	1	2	3	4	5	6	7	8
1	**0.962**	0.938	0.968	0.98	0.971	0.989	0.988	0.955
2	0.979	**0.981**	0.991	0.967	0.982	0.949	**0.977**	0.981
3	0.979	0.949	-0.851	0.968	0.929	0.899	0.959	0.976
4	0.99	**0.989**	0.498	0.618	0.939	0.929	0.989	0.944
5	0.936	0.949	0.688	-0.771	0.899	0.996	0.986	**0.957**
6	0.989	0.945	0.999	-0.014	0.931	0.967	0.982	0.972
7	0.999	0.998	0.958	-0.734	0.958	0.951	0.967	0.961
8	0.949	0.988	**0.977**	0.971	0.967	0.982	0.948	0.973

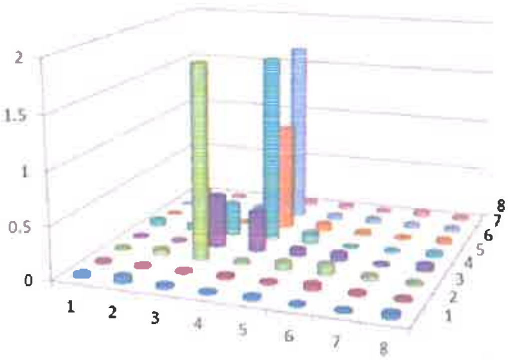


Figure 5: Changes and motion detection over inner blocks

In addition to changes over inner blocks, the total value of KLCC for images in Fig 3 is (0.7831). Following the same methodology, total KLCC values for the images in Figure 2 are illustrated in Table 4. Obviously, KLCC provides higher correlation (0.9641) for close images (3 and 4) than original CC (0.9426), and less correlation (0.7325) for far images (1 and 4) than original CC (0.7971). Generally KLCC values are spread in wider range than CC values, which provides higher distinguishing ability.

Table 4: KLCC values for images in Fig 2

	a	b	c	d
a	1	0.7831	0.8603	0.7325
B	0.7831	1	0.9314	0.8822
c	0.8603	0.9314	1	0.9641
d	0.7325	0.8822	0.9641	1

Different sizes of image blocks provide different results for KLCC. Bigger sizes consume less time and computational operations, yet, different areas can be included in single blocks. On the other side, smaller blocks provide more accurate determination for different areas consuming more time and computational operations. Experiences on the whole dataset images recorded better results when block size is (32×32) pixels.

Conclusions

Cross Correlation (CC) is standard measure which is used to explain the distances between two images. One of the most popular usages of CC is for sequential images. K-Local Cross Correlations (KLCC) provides more detailed information about the studied images, which are local CC's and the total correlation. In addition to the correlation between the two images, KLCC provides proposed detection for motion and changes over the two images. KLCC provides farer distances between CC values that have higher distinguishing abilities. Best recorded image blocks were (32×32) pixels.

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