ILLUMINATION INVARIANT INTENSITY-BASED IMAGE REGISTRATION USING CHAOS THEORY

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ABSTRACT

Accurate and robust registration of image pairs is of interest in many fields that use computer vision such as surveillance and medical diagnostics. In each of these fields the area-based (or voxel-based) approach to image registration is popular, however it is known that these methods are sensitive to illumination change where incorrect results are common. Past work in applying chaos theory to computer vision has demonstrated that the underlying physics of illumination change versus contextual change result in very different behavior when analyzed in phase space. Illumination is deterministic and results in non-fractal phase space behavior, while contextual change is chaos-like and results in complex fractal regions in phase space. A chaos-theoretic approach to image registration is presented with favorable results compared to the traditional and very popular Mutual Information measure.

Index Terms-- Image registration, Image sequence analysis, Chaos, Nonlinearities.

1. INTRODUCTION

Registration of two images is a common operation in applications such as multi-sensor image fusion for surveillance for object tracking and change detection and fields such as medical diagnostics for region of interest detection and isolation. There are many classes of registration algorithms, with a common taxonomy of methods being either Point based or Voxel (or Pixel) based, defined by Maes, et al. [10] as:

> "*Point based* methods rely on … landmarks or … geometrically salient points."
>
> "*Voxel based* registration methods optimize a functional measuring the similarity of all geometrically corresponding voxel pairs for some feature."

Algorithms that rely on feature point matching will not be addressed here since they do not have a direct phase space correspondence. As the voxel methods (also referred to as area-based methods in [12][11][16]) require a similarity measure, Mutual Information has been shown to be a very effective tool for this class of image registration algorithms [9]. The performance of the various algorithmic approaches depend heavily on the types of variations that are present in the image pairs being registered, and Oldridge restates Brown's taxonomy of variations into three classes: "(i) variations due to differences in acquisition that cause the images to be misaligned, (ii) variations due to differences in acquisition that cannot be easily modeled such as lighting, and finally (iii) variations due to movement of objects within the scene" [12][13]. Zitova and Flusser identify a number of weaknesses of area-based methods including, "classical area-based methods…exploit…image intensities, without any structural analysis. Consequently, they are sensitive to…*varying illumination*" [11]. Likewise the findings in the research efforts of a variety of researchers including Brown [13], Oldridge [12], Zitova and Flusser [11] all confirm it is difficult to separate the effects of image transformations from illumination.

Within this paper, the author will specifically confirm these findings and show that Mutual Information often fails to identify the correct image changes when illumination change is present. We will then present an alternative approach to image registration based on tools commonly employed in the field of chaos theory. It has been shown that non-linear dynamical systems often exhibit chaotic behavior [4]. Specifically, chaos-like behavior is defined as systems which exhibit interesting and complex behavior in phase space, and these chaotic phase plots can be characterized by their fractal dimension [4]. Phase space is simply the mapping of the amplitude of each pixel in an image against its relative change compared to the next image in the sequence. In this paper we demonstrate that image change due to translations have chaos-like behavior when analyzed in phase space, while the effects of illumination remain deterministic (non-chaotic); thereby making it possible to robustly differentiate illumination changes from the changes due to the either object or ego-motion in image registration.

2. FRACTAL AND NON-FRACTAL IMAGE EFFECTS

There are two elements to the image registration problem that a successful algorithm must provide: (i) sensitivity to detection of changes/transformations in the image, and (ii) insensitivity to the effects of illumination changes. Various researchers have modeled illumination changes as being a multiplicative effect [2], and under the simple Lambertian model, the scene radiance is:

$$L_m = \rho \vec{N} \cdot \vec{I} \cdot \lambda , \tag{1}$$

where λ is the external change to the illumination, L_m is the resulting radiance, ρ is the albedo of the surface, and $\bar{N}$ is the surface normal. The changes in radiance due to either ego-motion or motion of an object through the field of view result in *non-linear* multiplicative effects through the product of the surface normal with the illumination source. This has also been verified by Xu and Roy-Chowdury who state: "[the changes in the observed image] is a non-linear function of the [rotational and translational] motion variables" [3].

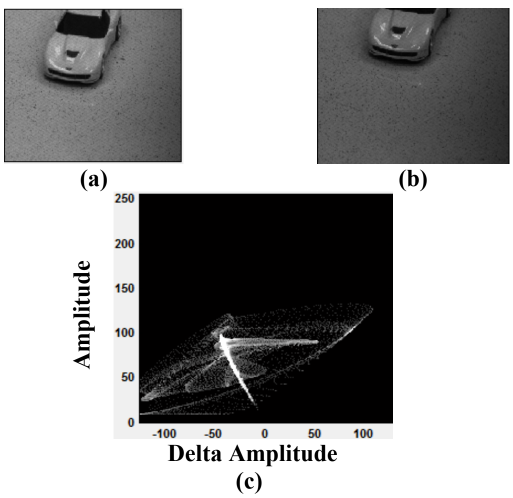


Figure 1: Chaotic nature of moving objects, (a) first image, (b) second image with motion and illumination change, and (c) resulting phase plot.

Peitgen, et al, states that chaotic behavior of dynamical systems can be detected in the phase plot of the system [4]. Figure 1 provides a laboratory illumination change sequence showing the chaotic effects in phase space due to a moving object with global illumination present. The diagonal bright line corresponds to the multiplicative shift in image amplitudes due to the illumination change. The broad remaining extent of the phase plot is due to the motion of the object in the scene. Figure 2 shows an ego-motion problem where the chaotic effects of this type of motion are also manifested in complex, i.e. space filling, behavior in phase space. Thus change between image pairs either due to moving objects or moving cameras relative to the environment exhibit interesting chaos-like behavior in phase space.

The distinctly different phase space behavior of illumination change versus motion shown in Figure 1 provides the chaos-theoretic foundation for solving Zitova and Flusser's issue of area-based methods being unable to deal with illumination change [11]. The deterministic structure of illumination change will result in a non-fractal phase plots; while the chaotic structure from image change will result in phase plots with high fractal values. In the next section we will discuss suitable measures for analyzing these phase spaces and how they favorably compare to the traditional Mutual Information measure.

3. CHAOS-BASED REGISTRATION BETWEEN IMAGE PAIRS

Note that mutual information is one of the most popular area-based measures for image registration, where, the mutual information between two images is defined as[9]:

$$I(A;B) = \sum_{a,b} p(a,b) \cdot \log\left(\frac{p(a,b)}{p(a)p(b)}\right), \tag{2}$$

where $p(a)$ and $p(b)$ are the distributions of images A and B, and $p(a,b)$ is the joint distribution of images A and B, and a is the intensity of a pixel in image A and b is the corresponding intensity of the same pixel in image B.

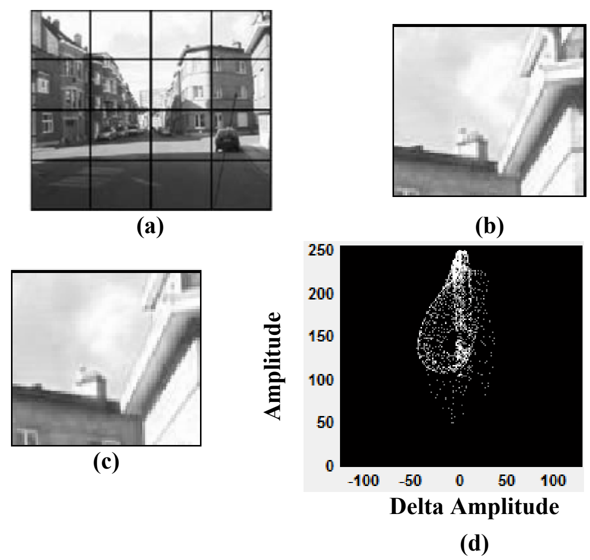


Figure 2: Chaotic nature of ego-motion, (a) entire scene, (b) upper left region of first image, (b) upper left region of second image, and (d) resulting phase plot.

While there are many interesting properties of mutual information, the following three are particularly useful for image registration of two images A and B: [9][17]:

$$I(A,B) = I(B,A) \tag{3}$$

$$I(A,A) = H(A) \tag{4}$$

$$I(A,B) \leq H(A) \tag{5}$$

Equation (3) establishes symmetry of the Mutual Information operator between two images. The property of Equation (4) establishes the upper bounds of the Mutual Information operator being the comparison of an image with itself. Equation (5) establishes the fact that by comparing any image with a different image the Mutual Information will be at most that of the image compared with itself and otherwise will be less than that value. This is a key parameter for using Mutual Information to search for optimal registration parameters as it establishes the rule that the result will always be *less than* that for a perfect match.

Fortunately, these key three properties also apply in the following manner in chaos-based analysis and the properties defined in Equations (4) and (5) are even simpler in definition. The chaos-based properties are defined in terms of the fractal dimension, F_D of the phase plots of the two images, A and B, as follows:

$$F_D\left(A_{\text{phase plot}}, B_{\text{phase plot}}\right) = F_D\left(B_{\text{phase plot}}, A_{\text{phase plot}}\right) \quad (6)$$

$$F_D\left(A_{\text{phase plot}}, A_{\text{phase plot}}\right) = 1 \quad (7)$$

$$F_D\left(A_{\text{phase plot}}, B_{\text{phase plot}}\right) \leq 2 \quad (8)$$

Additionally, the fractal dimension of a single point in phase space is zero. Equation (7) is because the phase plot of an image with itself generates a straight line and the dimension of a line is one and sets a lower bound for the fractal dimension between two images [4]. Thus the lower bounds on the registration value between two images are actually *independent* of the image being analyzed when applying the chaos-based approach. Likewise, the greatest difference between two images is also independent of the two images and only relies on the fact that the most complicated phase plot will completely fill the entire phase space, resulting in a dimension of two. Based on Equation (7), the process of image registration will be to find the transformation that *minimizes* the fractal dimension of the phase plot resulting from the first image and the transformed second image.

As with the Mutual Information measure we need a single value to describe the 'space-filling' nature of the phase plot resulting from comparing two images. Global measures of the fractality of the phase space plots provide such a measure. Two common global measures are the Box Counting dimension and the Information Dimension. These fractal measures are morphological-based dimension measures and are related to Hausdorff dimension, which is defined as [4]:

$$h_{\varepsilon}^{s}(A) = \lim_{\varepsilon \to 0} \left\{ \inf \left[\sum_{i=0}^{\infty} diam(U_i)^s \right] \right\}, \quad (9)$$

where $\{U_i\}$ is the set of hyper-spheres of dimension s providing an open cover of space A where the hyper-spheres are of $diam(U_i) < \varepsilon$. The Box Counting dimension, $dim_B(A)$, is an approximation of the Hausdorff dimension defined as [4]:

$$dim_B(A) = \lim_{\delta \to 0} \frac{\log N_\delta(A)}{-\log \delta}, \quad (10)$$

where $N_\delta(A)$ is the number of boxes of size δ that cover the phase plot A. The Information Dimension is based on Shannon's definition of the information content in a signal and measures the sum of the information across all boxes at a given resolution [7]:

$$S(\delta) = -\sum_i P_i \log_2 P_i, \ \text{where } P_i = \mu(B_i) / \mu(A) \quad (11)$$

where $\mu(A)$ is the total density of the phase plot and $\mu(B_i)$ is the density of the phase plot within box B_i. The Information Dimension is then defined to be [7]:

$$\dim_{\inf o}(A) = \lim_{\delta \to 0} \frac{-S(\delta)}{\log \delta} \quad (12)$$

The Box Counting method and the Information Dimension provide very similar, though rarely identical measures for the fractal dimension of a space when the space is created by a single underlying phenomenon.

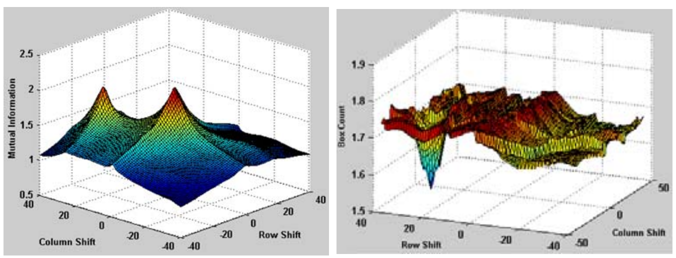
4. RESULTS

Recall Figure 1 , where both motion and illumination were present in the image sequence. Figure 3 (a) provides the search space for the detection of this object motion using Mutual Information. Notice that the peak of Mutual Information is at the origin meaning there were no translations detected. The Mutual Information search space has a smaller second peak which corresponds to the correct image translation parameters. Normalized Mutual Information has also been suggested for registration [17] but its results against illumination were identical in this case. There is no clear method for correcting Mutual Information against the presence of illumination, and this has been previously verified by other authors [12][13] [16].

Fortunately, the presence of illumination and motion present two distinct physical phenomena and hence result in very different behavior when viewed in phase space. Figure 3 (b) provides the decision surface for the Box Counting method, where the correct translation parameters occur at the minima since it is not affected by illumination. This is because the portion of phase space corresponding to illumination is very compact which results in little excursion and hence is virtually ignored by the Box Counting method. Unfortunately, the Box Counting method is sensitive to low amplitude large excursions which results in the complex search surface of Figure 3 (b) that can be difficult to search without a complex search algorithm. The Information Dimension, however, provides a fractal measure weighted by the frequency of the presence of the phase plot within any given region, and hence is expected to be less sensitive to these excursions as shown in Figure 4 (a). Note however, that the Information Dimension surface is again double-peaked.

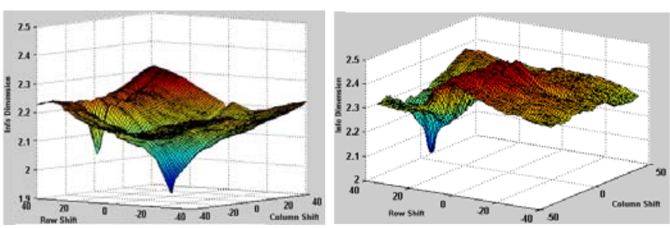
When occurring at the same time in an image pair, phase plots from these multi-phenomena situations will result in spaces that are *multi-fractal*. The non-fractal regions in a phase plot will lower the overall fractal dimension in the case of weighted measures such as the Information Dimension as can be seen in Figure 4 (a). This is because the measure captures the relative frequency of the phase plot within a box whereas Box Counting only relies on the binary decision of whether or not the phase plot is in a particular box. To minimize the potential impact of these non-fractal contributions there are three options to consider: (i) use the Box Counting measure, (ii) compute the *local* fractal dimension and segment the non-fractal components from the phase plot before computing the global dimension, or (iii) remove the non-fractal regions prior to calculating the fractal dimension based on the knowledge of their cause being illumination change.

When the phase plot in Figure 1(c) is pre-processed using the Mass Dimension which is a local measure [4], and the non-fractal regions are removed prior to the calculation of the Information Dimension, the search surface becomes that in Figure 4 (b). Notice this surface has the smoothness of Mutual Information and the single peak of Box Counting.



(a) (b)

Figure 3: Decision surface for area-based image registration, (a) using Mutual Information and (b) using Box Counting.



(a) (b)

Figure 4: Decision surface for area-based image registration, (a) using Information Dimension without illumination removal and (b) using Information Dimension with illumination removal.

Another case where Mutual Information fails is when there is only a small region within an image for performing registration. This can occur when tracking small objects in a scene or when there is considerable background in an ego-motion scene as shown in Figure 5 (a) and (b) with the phase plot shown in Figure 5 (c). In this image only a corner of a building is visible from the ego-motion application from Figure 2. The search space for using Mutual Information is provided in Figure 6 (a). As with illumination corruption, there again is a two peak search space. The primary peak corresponds to no translation in the image which is clearly incorrect. Figure 6 (b) provides the search space for the Information Dimension where the correct translation parameter is detected. For image pairs with extensive background relative to the region of interest, the Mutual Information measure is overwhelmed by the large number of background pixels much the same way it is overwhelmed by the presence of illumination change. The chaos-based methods proposed in this paper, however, are immune to these large regions of no change.

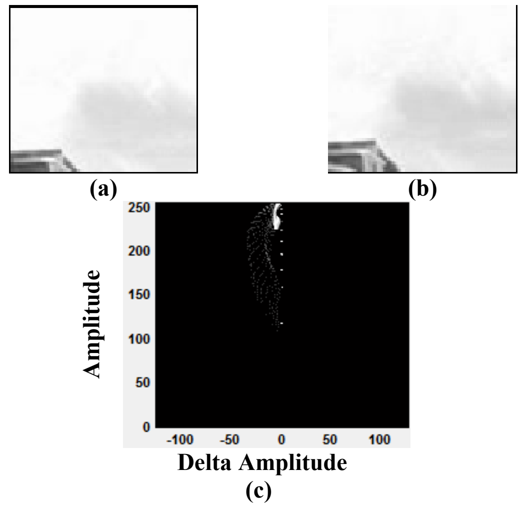
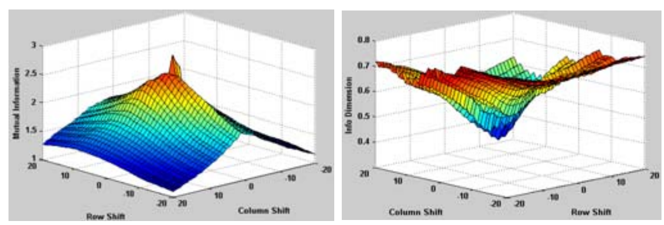


Figure 5: Chaotic nature of moving objects in a field of view, (a) first image, (b) second image, and (c) phase plot.



(a) (b)

Figure 6: Decision surface for area-based image registration, (a) using Mutual Information (b) using Information Dimension.

5. CONCLUSIONS & FUTURE WORK

In this paper we proposed a chaos-theoretic approach to area-based image registration. This approach was compared favorably to traditional Mutual Information-based measures. The chaos-based methods were demonstrated to perform superior to Mutual Information in situations where there is illumination change between the image pairs and in cases of extensive non-changing background. Sensitivity of area-based methods to illumination change has been noted by numerous authors but no solution has been proposed until this paper. The chaos-theoretic approach is founded on the fact that illumination and contextual change are easily differentiated when viewed in phase space. Using the Information Dimension with pre-processing to remove non-fractal effects due to illumination provided the best overall performance. Future work will address multi-modal image pairs where each image is from a different sensor.

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