Automatic Improvement of Image Registration Using High Information Content Pixels

Paula M. Tristan, Ruben S. Wainschenker and Jorge H. Doorn

Abstract— Image registration is currently used to refer the activity of make to coincide two or more observation of the same scene. This task is fundamental for several areas of image processing, such as: remote sensing, processing of medical images and video processing, among others. There are numerous publications addressing the image registration problem, from several points of view. It involves choosing one image as reference. The remaining images must be shift to match the one chosen as reference. Two images match between them whenever every region of the original scene is mapped on the same set of pixels in both images. The registration problem consists in finding the geometric transformation to accomplish the required modification of the image. Existing methods may be classified as: based on characteristics and based on areas. The first group of methods requires the intervention of an expert who chooses a set of distinctive points of the image, while the second group of methods automatically uses all pixels of the image. This does not take into account the fact that the information content of different pixels may be rather different. Pixels with low content of information degrade the contribution of the pixels with high information content. Information content is measured in relation with its contribution to define the geometric transformation. This paper details a method that automatically discards pixels with low content of information focusing the calculation on those with high information content.

***Keywords*—**Image Registration, Image Matching, Super-Resolution.

I. Introduction

In its simplest form, registration finds a unique correspondence between every pixel in one image to another pixel in a second image. It consists in finding the existing geometric transformation among two or more images of the same scene [1]; both pixels represent the same physical point on the scene. In many cases, the motion between different views of the same scene can be described by one of various parametric models [2]. For example, motion of a distant scene captured by a slowly moving camera contains only a two-dimensional (2D) translation. Satellite images or scanned documents undergo a similarity transformation which is a combination of a 2D translation, rotation and scaling.

The motion of a 3D planar surface or of a static scene captured by a pan-tilt-zoom and rotating camera is a 2D projective transformation. Image registration becomes a preprocessing for several areas of image processing like image fusion [12] [14], Super-Resolution applications [6] [7], video enhancing [8] and others. Application fields range from ambient studies [3] [4] [11] to patient monitoring [10], [22], [5] including many other fields. Granularity of registration may be at whole pixels or at sub-pixel level. Dividing actual pixels into a large number of equally sized virtual pixels, would permit to unify both pixel and sub-pixel registrations.

Image registration strategies can be divided into four main groups according to the manner of the image acquisition or to the purpose of the registration [9]: i) images captured at different times, ii) images captured from different points of view, iii) images captured by different sensors and iv) images processed in the context of different digital models. The last one is called scene-model registration.

The large collection of registration algorithm may be classified in two main groups: based on characteristics and based on areas. While the former just requires a set of pair of corresponding pixels, one pixel of the pair in each image; the latter uses the information from all pixels of the image or a portion of the image [9].

The pair of pixels used by the based on characteristics methods are usually referred as control points, meaning that they correspond with well known and distinctive points of the actual scene. One of the most desired virtues of the control points is the easiness for their identification in each frame of a sequence of images. Methods based on area use all pixels of the image or of a portion of the image. They compare all pixels of one image with the corresponding pixels of another image. More than one mapping may be possible. It is necessary to select the best one. A similarity metric have to be used for that purpose. Minimizing or maximizing this metric, allows determining the best mapping among both images [2]. The quality of the registration relies on how well the metric fits with the image comparison problem. Distance between images or similarity coefficient are valid metrics [16]. The main drawback of this sort of methods resides in their own conception: they may only succeed in the context of simple shifts or when the deformation pattern is well known. Images containing more complex deformations will require many local registrations instead of a global one and even this is not always possible.

An important weakness of the methods based on areas is related with the presence of large homogeneous regions in both images. Such lack of variation in those regions increases the degree of uncertainty of the metric used. This may become also worse when noise is present. Noise creates random patterns in quasi-homogeneous regions. There the metric may tune patterns up rather than the regions themselves. This implies the necessity of choosing the window where registration is going to be applied [2]. How to qualify which regions may be used and which not also leads to the pixel selection strategy detailed below.

Due to the nature of its approach, the methods based on characteristics are far from being robust. They are limited to pixel-level registrations and also tend to produce results with excessive errors. They are very sensible to the adequacy of the pixel selection done by the expert. To cope with this inconvenience it is necessary to increase the number of pixels used. On the other hand, methods based on areas provide registrations of a similar quality among them with better repetitiveness. Many authors have suggested the alternative of completing a registration process by first applying a feature-based registration and then refine it using some method based on area [1] [9] [19] [20].

The method proposed in this article does not use similarity metrics. This is an additional advantage since the solution has no dependence on a metric criterion.

Pixels are chosen or discarded in base to their ability to contribute to estimate the displacement. This displacement is then calculated using a set of special pixels.

The rest of the article is organized as follows: the foundations of the proposed method are presented in the next section. The criteria to choose reach information pixels are described. Finally, obtained results are shown and conclusions are derived.

II. Fundamentals

This proposal is based on the supposition that, for a given scene, every image involved in the registration was obtained by a digital sampling of a continuous domain function [17]. This function models the light intensity distribution arriving from the actual scene. Input signal **f(x,y)** undergoes bandwidth reduction by the combination of lenses and aperture. For classical digital capturing devices an inverted image is projected over the imaging plane. The signal is sampled by light integration over finite-size sensor elements. The signal given by each sensor is quantized to form a digital image **g[i,j]**. It should be remind that the relationship between **f(x,y)** and **g[i,j]** may or may be not lineal. This depends upon the internal characteristic of the transductor. Although sensor blur and sampling may occur simultaneously, they are depicted here as separate processes for clarity purposes. Besides the mentioned degradations, the output image also may suffer from noise and aliasing (See Fig. 1).

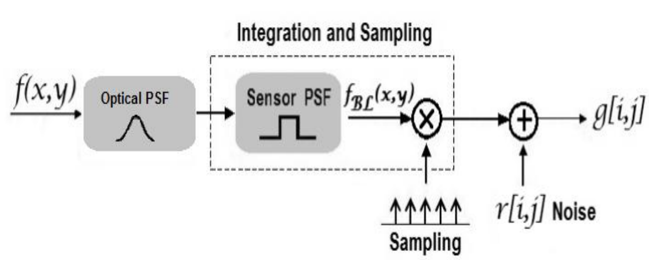

Fig. 1 standard process of image capture

The actual scene captured by the sensor is modeled by this function. It is important to notice here that it is supposed that this function is unique for all images. All differences among images are attributed to how this function was sampled. The proposed method performs a numerical approximation of such functions. As a consequence, any pixel of one image may be estimated using the value of corresponding pixels of other image. This supposition fits with most actual registrations applications. However, some portions of the observed scene may contain intrinsic variations such it may happens with a change of illumination in a video sequence or a cover evolution in a sequence of satellite images. In these cases the method proposed may be still successfully applied. This issue will be discussed in section IV.

Let $P_o[x_o,y_o]$ be a point of the scene located in the upper left corner of the pixel $g_r[i_o,j_o]$ of the image taken as a reference. Using Taylor theorem, if **f(x,y)** is differentiable in a region containing P_o, for small values of α and β it can be expressed:

$$f(x_0+\alpha, y_0+\beta) = f(x_0, y_0) + \left.\frac{\delta f}{\delta x}\right|_{P_0} \cdot \alpha + \left.\frac{\delta f}{\delta y}\right|_{P_0} \cdot \beta + \frac{1}{2}\left.\frac{\delta^2 f}{\delta x^2}\right|_{P_0} \cdot \alpha^2 + \left.\frac{\delta^2 f}{\delta x \delta y}\right|_{P_0} \cdot \alpha\beta + \frac{1}{2}\left.\frac{\delta^2 f}{\delta y^2}\right|_{P_0} \cdot \beta^2 \ldots \quad (1)$$

The pixel value is the result of the integration of f(x,y). (1) helps to understand physical integration during the capture of images. It allows deducing which properties must have f(x,y), and as a consequence the related images pixels, to make them useful to estimate α and β.

When several (g_r, g_s, …, g_t) images to be registered have sub-pixel level displacement with g_k, bilinear interpolation is frequently used to approximate the relationship existing among (g_r, g_s, …, g_t) and g_k pixels:

$$g_k[i_0, j_0] = (1-\alpha)\cdot(1-\beta)\cdot g_r[i_0, j_0] + (1-\alpha)\cdot\beta\cdot g_r[i_0, j_0+1] + \alpha\cdot(1-\beta)\cdot g_r[i_0+1, j_0] + \alpha\cdot\beta\cdot g_r[i_0+1, j_0+1] \quad (2)$$

The classical interpretation of (2) states that the energy provided by every pixel comes from a distributed source with the property of being homogeneous over the whole pixel.

Usually it is omitted that this will be true only for linear transductors (see Fig. 1). Under such interpretation, the average intensity of a shifted pixel can be determined by the composition of the intensities of the pixels of the reference image weighted by their fraction of surface. Integrating (1) for the pixels involved in (2), it can be seen that (2) has no error as long as the terms in α^2 and β^2 and superior are null. This allows extending previous interpretation to any source with no curvature in both axes. This change in the interpretation notably increases the number of underlying functions for which the bilinear interpolation does not introduces any error.

A special case appears when f(x,y) is not differentiable but the discontinuity is located near to a pixels edge. In other words, this case appears when a homogeneous pixel of the reference image has on its side another homogeneous pixel with a rather different intensity value. In the field of image processing this can be expressed saying that the reference image has a sharp border with no transition pixels. This border is almost horizontal or almost vertical. As a consequence, homogeneous pixels and sharp edges in the reference image will match with non homogeneous pixels with diffuse edges in the image being registered. Even though any image may be chosen as reference, those with more sharp edges become preferable for this case. See vertical and horizontal shifts in section III.

III. The Proposed Method

As mentioned before, the proposed method is based on the supposition that the reference and the image to be registered were created by means of numerical approximations of the same underlying continuous function f(x,y).

Let g_r and g_k be two images of the same scene with $\vec{\delta} = (\alpha, \beta)$ a sub-pixel shift between them. Using bilinear interpolation to approximate the relationship between g_r and g_k as indicated in (3).

$$g_k[i,j] = (1-\alpha)(1-\beta)g_r[i,j] + (1-\alpha)(\beta)g_r[i,j+1] + (\alpha)(1-\beta)g_r[i+1,j] + (\alpha)(\beta)g_r[i+1,j+1] \quad (3)$$

Grouping terms containing α, β, and αβ, (3) becomes:

$$R_{i,j} = M_{i,j}\alpha + N_{i,j}\beta + H_{i,j}\alpha\beta \quad (4)$$

Where:

$$R_{i,j} = g_k[i,j] - g_r[i,j] \quad (5)$$

$$M_{i,j} = g_r[i+1,j] - g_r[i,j] \quad (6)$$

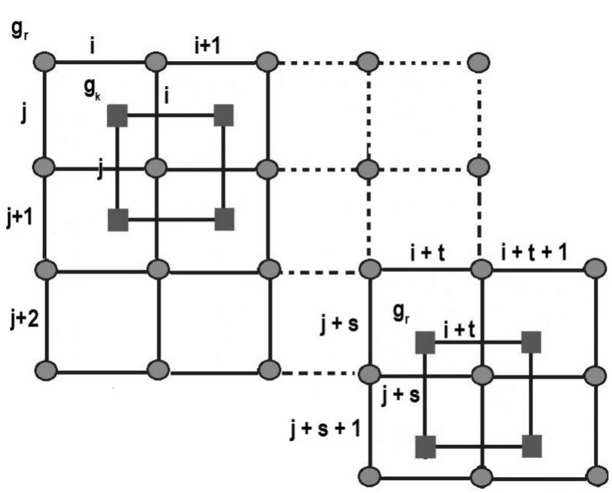

Fig. 2. Possible pairs of pixels from a whole image.

$$N_{i,j} = g_r[i,j+1] - g_r[i,j] \quad (7)$$

$$H_{i,j} = g_r[i,j+1] - g_r[i,j] - g_r[i+1,j+1] + g_r[i+1,j] \quad (8)$$

M, N and H are the discrete estimations of the derivatives δf/δx, δf/δy and $\delta^2 f/\delta x\delta y$ of (1).

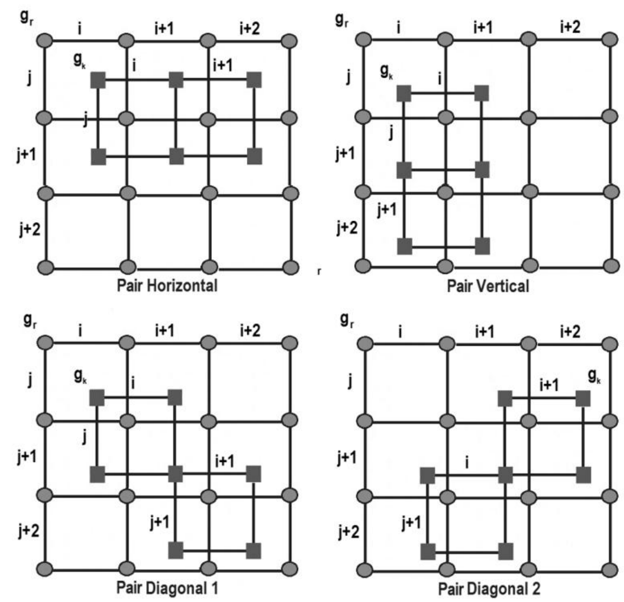

Fig. 3 Possible pairs of adjacent pixels from a nine pixel subset

(4) describes a problem with two unknowns which may be solved applying it to a pair of pixels of the image to be registered. For any pair of images g_r y g_k of u = (m-1)(n-1) pixels, up to u(u-1)/2 solutions may be obtained. If f(x,y) is differentiable over the whole image, every pair pixels would give a valid solution (Fig. 2). For simplicity it is better to choose adjacent pixels as shown in Fig. 3.

A. Pixel selection criteria

A simple test of (4) on an arbitrary set of nine pixels (Fig.3) shows that apparently good results can appears accompanied by invalid ones. To determine which pixels allow a better estimation of α and β, it is required returning to (1) and (2) since better pixels are those with the property f(x, y) that terms in α^2 and β^2 and superior order are locally null. Unfortunately, these conditions have two weaknesses: i) They are necessary but not sufficient, and ii) its verification is not immediate. The fact that such condition is not sufficient can be easily seen considering what would occur in any of the possible pairs of equations shown in Fig. 3 when they are applied to a homogeneous region larger than several pixels. If so happens, M, N, H and R of (5) to (8) are null. As a consequence, none of possible systems of equations would provide an estimation of α or β.

Considering that the quantization of pixel values only discriminates a few hundred of intensities, values of M, N, H and R close to 0, $M \approx N \approx H \approx R \approx 0$, would let to calculate α and β, but with a large dispersion, which make them unusable. As a consequence of this, it can be concluded that at least one of the terms in α, β or αβ must be rather different from zero.

From all possible instantiations of (4), it is here proposed to choose only those providing as much information about the value α, β or both as possible.

Fig.4 Pixels without shift information

Here it is important to be aware that the rejecting condition, $M \approx N \approx H \approx R \approx 0$, discards a large quantity of pixels in most of actual images. Fig. 4 depicts those pixels that neither allow to estimate α nor β in black for strawberries image taken from Gonzalez and Woods [19]. The percentage of rejected points only by this condition is over 45%.

The following sections describe how the previous properties may be written in terms of observable pixel values.

1) Vertical shift (β)

(4) would allow to estimate the vertical shift (β) regardless the horizontal shift when $M_{ij} = H_{ij} = 0$ and $|N_{ij}| >> 1$. These conditions must occur at least on one of the instances of (4). When it is true on both instances $M_{i1j1}=H_{i1j1}=M_{i2j2}=H_{i2j2}=0$, $|N_{i1j1}| >> 1$ and $|N_{i2j2}| >> 1$, two different estimations of β will be obtained. Fig. 5 depicts dots all pixels that allow estimating β for strawberries image.

Condition $|N_{ij}| >> 1$ is still ambiguous. No specification about how much is “rather larger than 1” was given. This condition may be rewritten as: $|N_{ij}| > k_1$. It is important to notice that larger values of k_1 produce less error in the estimation of β but excludes many potentially valid pixels. This reduces the statistical quality of the estimation. On the other hand smaller values of k_1 let to collect many points but the individual quality of the result provided by them is poorer. There is a clear compromise between the quantity of pixels chosen and the individual quality of the estimation of β. This compromise is controlled by minimum value accepted for $|N_{ij}|$. Every image has a value for k_1 that provides the minimum variance for β.

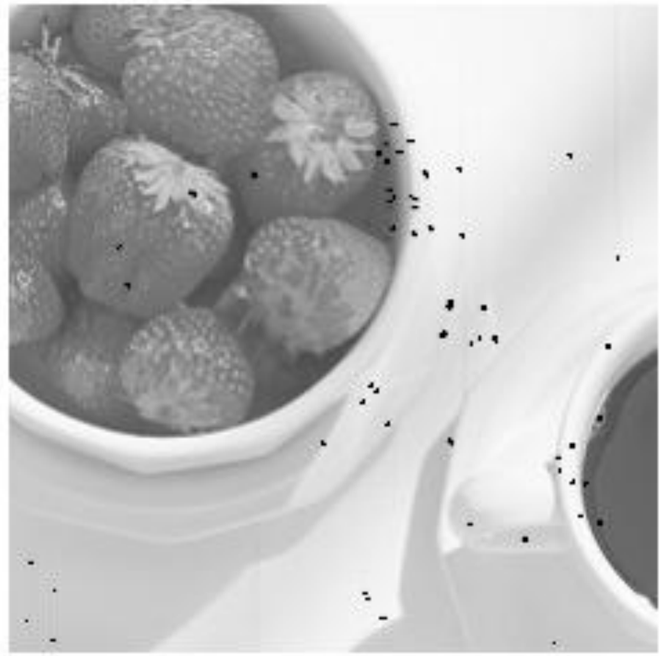

Fig.5 Pixels with vertical shift information

2) Horizontal Shift (α)

As it happens for the vertical shift a single estimation of α may be obtained when $N_{ij} = H_{ij} = 0$ and $|M_{ij}| >> 1$, or a pair of estimations when $N_{i1j1}=H_{i1j1}=N_{i2j2}=H_{i2j2}=0$, $|M_{i1j1}| >> 1$ and $|M_{i2j2}| >> 1$. Fig. 6 depicts all pixels that allow estimating α in strawberries image.

Here, condition $|M_{ij}| >> 1$ is also ambiguous. A limit value c for $|M_{ij}|$ must be defined. There is a compromise between the quantity of pixels chosen and the quality of the individual quality of the estimation of α too. This compromise is controlled by minimum value accepted for $|M_{ij}|$. Every image has a value k_1 that provides the minimum variance for α.

3) Vertical and horizontal shifts combined

In most image registration situations, the previous conditions provide hundreds of pixels with high information content, which give good estimations of α and β. Exceptionally it may occur that the number of pixel satisfying the conditions are few. This happens especially in satellite images. When it is required another group of pixels with high information content, they may be found as follows: i) a good estimation of β can be obtained when the value of $M_{i,j}$ is near to zero for a pair of pixels, ii) on the opposite, a good estimation of α can be obtained when the value of $N_{i,j}$ is near to zero for a pair of pixels.

a) $M_{i_1j_1} \approx M_{i_2j_2} \approx 0$, $|N_{i_1j_1}| >> |M_{i_1j_1}|$, *and* $|N_{i_2j_2}| >> |M_{i_2j_2}|$.

Here it can be estimated both α and β, however only values of β will be reliable.

b) $N_{i_1j_1} \approx N_{i_2j_2} \approx 0$, $|M_{i_1j_1}| >> |N_{i_1j_1}|$, *and* $|M_{i_2j_2}| >> |N_{i_2j_2}|$

Also, here it can be estimated both α and β, being reliable

Fig. 6 Pixels with horizontal shift information

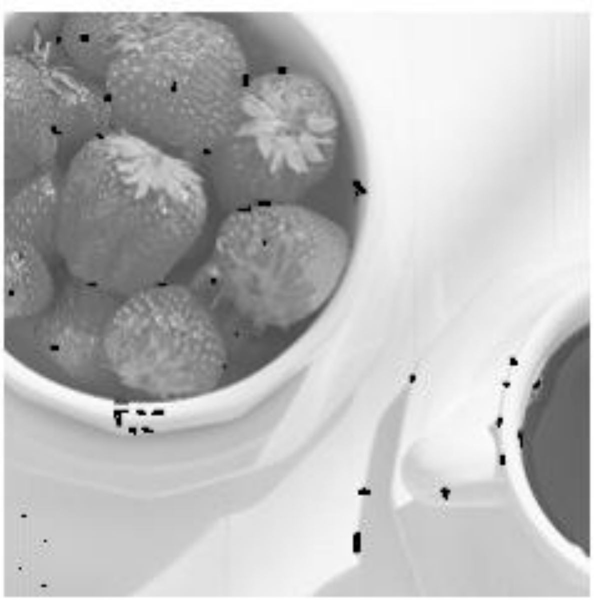

Fig. 7 Pixels that allow estimating α and β

Fig. 7 depicts all pixels that allow estimating α and β in strawberries image. Here condition $|N_{i1j1}|>>|M_{i1j_1}|$, and $|N_{i2j2}|>>|M_{i2j2}|$ for case a) and $|M_{i1j1}|>>|N_{i1j1}|$, and $|M_{i2j2}|>>|N_{i2j2}|$ for case b) must be considered in a similar way as it was done in subsection 2) for $|N_{ij}|>>1$ and in subsection 3) for $|Mij|>>1$.

Previous conditions must be rewrite as:

a) $|N_{i_1j_1}| / |M_{i_1j_1}| > k$ *and* $|N_{i_2j_2}| / |M_{i_2j_2}| > k_2$.

b) $|M_{i_1j_1}| / |N_{i_1j_1}| > k$ *and* $|M_{i_2j_2}| / |N_{i_2j_2}| > k_2$.

Here, larger values of k_2 produce less error in the estimation of α or β but exclude many potentially valid pixels. The compromise is between the quantity of pixels chosen and the individual quality of the estimation of α or β. This compromise is controlled k_2. Every image has also a limit for k_2 that provides the minimum variance for α or β.

When using 2), 3) and 4) combined, the compromises must be combined too. There is a pair of values k_1 and k_2 that allows getting the best estimation of α and another pair for β. In actual images cases 2) or 3) provides more than 80% of valid pixels while case 4) provides less than 20%.

4) Testing images

To evaluate a registration method it is necessary to have a set of images shifted respect of a reference image and a metric to quantify the quality of the registration performed. Since in most cases this set of images is not available, it must be built for the experiment. Frequently this image set is created shifting an image using numerical methods. Testing a registration strategy using such set of numerically shifted images leads to obtain unrealistic results. Actually, this sort of image set does not provide a reliable testing environment. Numerically shifted images have embedded the bias created by the shifting algorithm itself, and this bias is propagated to any result obtained with them.

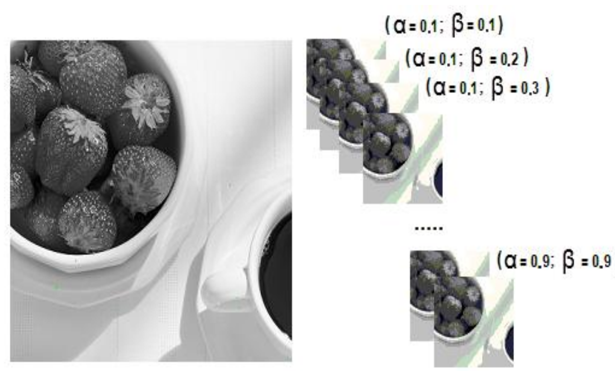

Fig.8 High resolution strawberries image and 81 low resolution images created according with Tuan proposal

Tuan in [2] proposed the use a better image sequence by means of decreasing the resolution of a high resolution image, averaging a large number of high resolution pixels to obtain a single pixel of the low resolution image. Strictly this averaging would model any actual image shifting only when the capturing device has linear transducers. Otherwise averaging may not have physical meaning and the transducer response should be involved in the low resolution image creation. Two different low resolution images obtained by means of the same average granularity but shifted in a whole number of pixels on the high resolution image produce would have a sub-pixel shift among them. This numerical procedure fits within the hypothesis of the model of Fig. 1, with no noise r(t). Tuan proposal was used creating one pixel of the low resolution every hundred pixels of the high resolution image. This allows handling testing values for α and β from 0 to 1 with a step of 0.1.

Fig. 8 shows a set of 81 low resolution images built using Tuan proposal for strawberries image. The first image was created using α = β = 0.1, the second one with α = 0.1 and β = 0.2, while the last one have α = β = 0.9. Every single image was registered to a reference image built using α = β = 0 using several registration methods and comparing their results with the pixel selection criteria algorithm proposed in this article.

IV. Results and analysis

As shown in tables I through IV, two important results were obtained:

1) A reduction in the variance of the estimation of α and β, and
2) A reduction in the absolute error in the estimation of α and β.

The first important result is shown in Table I and Table II. Correlation stands for Pearson correlation coefficient, while MSE refers to the Median Square error or the average of the square of the difference between the intensities of the pixels of both images (the image being registered and the reference one), SSIM represents Wang et al [16] Structural Similarity Index Metric and IQI is the universal Image Quality Index introduced by Wang and Bovik [18]. IQI and SSIM are near one to each other since IQI corresponds to a special case of SSIM. The standard deviation of the proposed method (last row in both tables) for α and β is notably lower than those obtained from all other tested methods.

The estimated values for α or β are closer to the exact value than the estimations provided by other methods. Table III and Table IV display such results.

Table I through Table IV talk by themselves, pixel selection algorithm provides better estimations of α and β shifts. Pixel selection algorithm was applied in many other contexts such as in Lena and other public domain and private images. In all the studied cases it showed better results than other registration methods. Sometimes the differences in the estimation error were larger and sometimes they were smaller.

TABLE I
ALPHAS ESTIMATIONS

Method	Standard Deviation
Correlation	0,0622
MSE	0,0745
SSIM	0,0785
IQI	0,0784
Selected Pixels	0,0335

Standard deviation of estimations of α.

TABLE II
BETAS ESTIMATIONS

Method	Standard Deviation
Correlation	0,0622
MSE	0,0686
SSIM	0,0676
IQI	0,0680
Selected Pixels	0,0379

Standard deviation of estimations of β.

TABLE III
ALPHAS ESTIMATIONS

Method	Absolute Error	Relative Error
Correlation	0,0162	5,54%
MSE	0,0181	6,31%
SSIM	0,0194	6,81%
IQI	0,0193	6,77%
Selected Pixels	0,0148	3,51%

Average absolute and relative error of estimations of α.

TABLE IV
BETAS ESTIMATIONS

Method	Absolute Error	Relative Error
Correlation	0,0185	0,0601
MSE	0,0200	0,0648
SSIM	0,0206	0,0657
IQI	0,0206	0,0657
Selected Pixels	0,0167	0,0366

Average absolute and relative error of estimations of β.

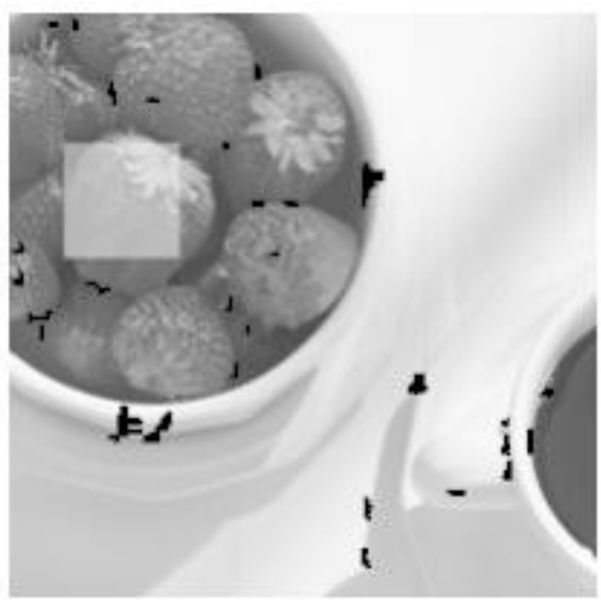

Fig.9 Strawberry image with a simulated large pixel variation in a large area of the image

TABLE V
ALPHAS ESTIMATIONS

Values	Estimate without pixel variation	Number of Pixels	Estimate with pixel variation	Number of Pixels
0,2	0,185	12	0,185	12
0,4	0,412	14	0,416	13
0,6	0,591	22	0,594	21
0,8	0,801	17	0,801	17

Analysis of estimations with and without pixel variation of α

TABLE VI
BETAS ESTIMATIONS

Values	Estimate without pixel variation	Number of Pixels	Estimate with pixel variation	Number of Pixels
0,2	0,189	4	0,189	4
0,4	0,410	12	0,389	11
0,6	0,615	7	0,615	7
0,8	0,780	6	0,780	6

Analysis of estimations with and without pixel variation of β.

Portions of the observed scene may contain intrinsic variations such as those due to a change of illumination in a video sequence or a cover evolution in a sequence of satellite images. In that cases all pixels included in these regions will provide unrealistic results. This usually result in values of α, β or both outside the expected range (0,1). When the scene change is minor, two possible indicators may be considered: i) the variance of the distribution of the values of α, β, or both is larger (this happens for large areas with minor changes), ii) the distribution of the values of α, β, or both contain a few outliers (this happens for small areas with minor changes).

Whenever it is possible, scene change regions should be identified and removed from the registration calculation. Small regions are easier to identify by means of pixels giving unrealistic results or by the presence of outliers in the distribution of α, β or both. Large regions will demand clustering strategies based on pixels giving unrealistic results or extreme values for α, β or both. It should be noticed that other method tested do not provide any indication at all to consider a possible variation in the studied scene. Fig. 9 depicts strawberries image with a simulated large pixel variation in a large area of the image. It should be noticed that no pixel were selected from this region. The estimation for α and β are quite similar to those with no underlying f(x,y) variation as shown in tables V and VI. These tables show the results of applying the pixel selection criteria to both images with and without pixel variation. The existence of such modified region in f(x,y) only produces a small reduction in the number of valid points available.

V. CONCLUSIONS

An algorithm to improve the registration parameters has been developed. This improvement is shown by a precise estimation of the parameters and by a reduction on standard deviation of the obtained values. It showed in many cases a better performance than other well known methods. This improvement in the registration parameter estimation comes from the fact that only high information content pixels are used during the registration.

This algorithm may be classified as hybrid due to its nature. On one side it can be seen as based on areas method since it scans the whole image to perform the registration but on the other hand it can be seen a based on characteristic method since it only uses a few pixel of the image. The best feature of this algorithm is that it takes advantage of both types of methods without the need of a manual identification of significant pixels of the image.

It is also remarkable that the algorithm is robust in the presence of important intrinsic scene variations, denoted by important changes in the underlying f(x,y). This allows dealing with images with sudden variations in the illumination due to reflected light or any other sources.

VI. FUTURE WORKS

The results already obtained lead to the hypothesis that better estimations of the registration parameters can be obtained using symmetric differences as estimations of both first and second derivates. This hypothesis is under testing.

It is unknown the influence of the granularity used when applying Tuan's partition on the quality estimation of any registration method. Currently, new strategies to create even better sets of images for testing are under consideration.

The use of more complex interpolation formulas instead of (2) and extensions to more complex registrations such as rotations and elastic transformations are planned.

The impact of the use of bilinear interpolation based algorithm on images obtained with currently available non linear transducer will be also analyzed.

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Paula M. Tristan holds a Master degree in System Engineering, UNICEN, Universidad Nacional del Centro de la Provincia de Buenos Aires, Argentina. Currently / at present, she is PHD student in Computer Science at UNICEN. Her main focus of attention on research is related to the image processing area. (phone: +54 2293 439682 ext. 49; fax: +54 2293 439682 ext. 23; e-mail: ptristan@exa.unicen.edu.ar).

Ruben S. Wainschenker, is professor at Departamento de Computación y Sistemas in Universidad Nacional del Centro (UNICEN). He holds a PHD in Physics Sciences obtained at the Universidad Nacional de Buenos Aires. His research interest includes signal processing focusing on algorithms to extract information from signals. (e-mail: rfw@exa.unicen.edu.ar).

Jorge H. Doorn has been full professor at Departamento de Computación y Sistemas in Universidad Nacional del Centro (UNICEN), since 1989. He has wide experience in industrial applications. He was leader/ director of several research projects; at present, he is head of the signal processing research group. (e-mail: jdoorn@exa.unicen.edu.ar).