Evaluation of Similarity Measures in Contrast Enhanced Echocardiography Motion Detection and Registration

EP Rodrigues, LO Murta Jr

Universidade de São Paulo, Departamento de Física e Matemática, Ribeirão Preto, São Paulo, Brasil

Abstract

In the present work, a similarity metric based on image difference entropy has been investigated for myocardial contrast echocardiography non-rigid registration. The image histogram size has shown to influence registration accuracy, improving results for difference entropy, which has presented better results when compared to other two well known similarity metric in literature, namely, normalized cross correlation and mutual information. The displacement field has been smoothed with a Gaussian convolution, allowing controlling the smoothness in geometric transformation and attenuating displacement field miscalculations. Therefore, registration parameters can be set to privilege more local or global image transformation. Difference image entropy has shown robust accurate registration for myocardial contrast echocardiography at parameter values found in this study.

1. Introduction

The image registration is one of the fundamental basic functions in medical imaging, allowing automatic or semi-automatic images alignment, useful for supporting diagnostic facilities in different kinds of diseases and clinical research. Registration makes possible the image fusion, which can be applied to an anatomic high spatial resolution image and a functional image alignment, allowing a simultaneous visualization. In the case the studied human organ has some movement constrains, such as brain, constrained by the skull compartment, the considered geometric transforms for registration are only rotation and translation. A scaling in image formation is also possible, due to modality scales differences. A more sophisticated case is when an organ has no such constrains and can deform in elastic way, making the registration procedure more complicated. In some studies, as the myocardium perfusion evaluation [1], a sequence of heart ultrasound with contrast agent image frames must be registered, to reach pixels correspondence and therefore correcting blood flow evaluation. Although these images have structures more defined than usual ultrasound due to the contrast, they are still noisy and at low spacial resolution, making it hard to register, therefore, registration procedure must be robust enough to deal with noise, low spatial resolution and elastic deformation to work. In order to register these images, it has been proposed a region matching algorithm with difference entropy (DE) similarity metric to drive the transformation which aligns myocardial contrast echocardiography (MCE) frames sequence to a frame selected as template. DE similarity metric have been evaluated previously for rigid body registration only [2, 3] and an elastic deformation of myocardial was registered by the proposed method. Since heart movements includes rotation, influence of parameters in registration accuracy, the limit it works for image rotations has also been tested. Results from DE similarity metrics has been compared to normalized cross correlation (NCC) and mutual information (MI) [3].

2. Methods

This section describes the registration methodology, DE similarity metric, the registration parameters and the error evaluation used to quantify registration accuracy. According to nomenclature adopted in this paper, I_T is the target image referred here as template image and I_F is the source or floating image to be registered.

2.1. Difference entropy

The histogram H of difference image I_D is calculated within values range of $[-255, 255]$. This range is shifted to $[0, 510]$ and then the histogram is re-sampled to fit h numbers of bins, since it influences the quality of registration result [4]. The difference entropy is defined by

$$DE = \frac{1 - \sum_{i=0}^{h-1} p_i^q}{q-1}, \tag{1}$$

which $p_i = H_i / \sum_{i=0}^{h-1} H_i$. The equation (1) represents the generalized entropy, and classic Shannon's entropy

$-\sum_{i=0}^{h-1} p_i \ln p_i$ is recovered from it when $q = 1$ [5]. The q value has been tested to verify impact in registration. Basically, when $q > 1$, entropy privileges high p_i values (high probability states). For parametric values $q < 1$, the lower probability states (low p_i) are privileged, and for $q = 0$ no p_i is privileged. The first situation have little meaning for echocardiographic image registration and the last two have no meaning. As a similarity metric, the DE finds its minimum value at the most similar region displacement.

2.2. Regions matching

A square region of size $2s+1$ (named searching window sw) placed at a fixed position centred at (i, j) on I_T, scans over I_F inside a searching region R of size $2r + 1$ also centred at (i, j), ranging from $[i-r, i+r]$ to $[j-r, j+r]$. At each R point, regions inside sw over I_T and I_F are subtracted and DE are calculated. The position for minimum DE defines a displacement vector $(\delta s_i, \delta s_j)_{(i,j)}$ regarding (i, j). A set of these vectors defines the displacement field $D_l(i, j)$, with $(D_1(i, j), D_2(i, j)) = (\delta s_i, \delta s_j)_{(i,j)}$

2.3. Registration

A set of points (m, n), with a regular interval size g is sampled over the images and the $D_l(m, n)$ is calculated. Limits are defined near images boundaries, and image is padded to zero beyond it. This procedure was adopted for boundary conditions. To smooth discontinuity in displacement field, the $D_l(m, n)$ is convoluted with a square Gaussian kernel of size $2a + 1$ pixels and variance σ^2, considering mirror symmetric condition adopted when accessing values out of boundaries. To register images, $D_l(m, n)$ is interpolated by bicubic Spline [6], resampling displacement field in $S_l(i, j)$ at each image pixel (i, j). Floating image is then interpolated, resulting in I_S. The registered image I_R is defined by following equation.

$$I_R(i, j) = I_S((i, j) + (S_1(i, j), S_2(i, j))), \qquad (2)$$

with (i, j) covering the entire image.

2.4. Registration parameters

In this study we used seven parameters to evaluate registration. A set of experiments were done in order to assess the impact of these parameters in registration, estimating influences from more local or global transformations. The parameters are described as following.

s - searching window size. Controls range in registration procedure, which can be local for lower s values, or global for high s values.

r - searching region size. Sets the maximum horizontal and vertical displacement considered in search for similar regions.

g - spatial gap between sampled points. Sets the number of sample points on the image. Local correction is privileged as g and s decreases.

a - smoothing kernel size. The range of Gaussian convolution process.

σ - smoothing Gaussian variance. This value regulates smoothing strength.

q - generalized entropy parameter. See section 2.1.

h - histogram number of bins

2.5. Registration error

An elastic deformation field $K_l(m, n)$ is interpolated and applied to an image $\mathbf{I}$ producing a transformed $\mathbf{I}_k$ in order to evaluate registration error. The $\mathbf{I}_k$ is then registered to $\mathbf{I}$ by calculating a displacement field $D_l(m, n)$, which is supposed to be close to $K_l(m, n)$ in case of successful registration. The error E is then calculated by the sum of averaged quadratic differences of displacements in image rows and columns as follows

$$E^2 = \frac{\sum_{l=1}^{2} \sum_{m=0,n=0}^{M-1,N-1} (D_l(m, n) - K_l(m, n))^2}{(M \times N)} \qquad (3)$$

where the M and N are the numbers of rows and columns of the displacement field.

2.6. Images

The image registration procedure has been applied and tested in a set of experimental MCE images obtained in parasternal short axis views at mitral valve, papillary muscles and apical levels in an animal model of acute myocardial infarction.

3. Results

In order to investigate the behaviour of registration accuracy for different parameter values, four different experiments were designed. In first experiment, a comparison has been made between NCC and MI. A pair of heart frames moving sequence were registered for various values of s and histogram number of bins h to assess its influence to MCE image registration, the remaining parameters was set to $r = 40$, $g = 10$, $q = 1$, $a = 5$ and $\sigma = 1$. The frames were selected between systolic and diastolic images, which have high displacements. The Fig. 1 shows the experiment result for $h = 15$ and $h = 256$. The $g = 10$ has been found to be the optimum accuracy and time performance simultaneously. As h increases, time consumed in registration increases. h value has been considered 15 for all designed experiments. Furthermore, lowering g does not ensure better results.

To privilege local alignments in first experiment illustrated in Fig. 1, the smoothing parameters a and σ was set

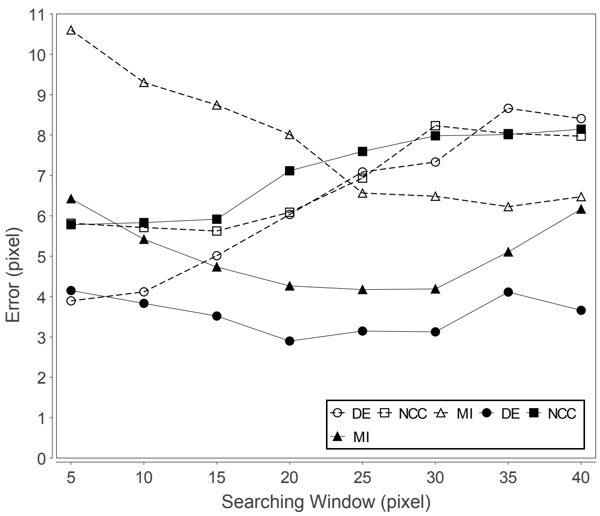

Figure 1. Registration error as a function of searching window sixe s for three similarity metrics and two histogram size h. The dashed line is for $h = 256$ and $h = 15$ for the solid one.

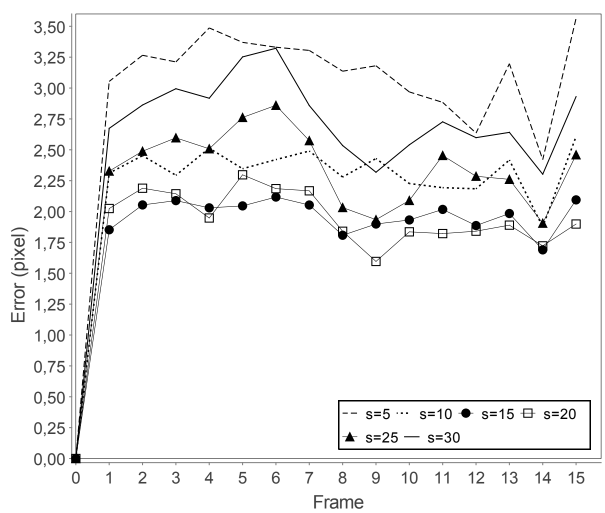

Figure 2. Registration error as a function of frame sequence registration for some s parameters. The frame 0 is the template and has therefore error equals 0 as it is registered to itself.

to privileges only small neighbours regions. If registration takes more than one stage, i.e, iterative registration, these values can be set to higher values and, as a consequence, the smoothing affects registration more globally, making the displacements more smoothed.

In the second experiment, Fig. 2 shows DE error in registration versus searching windows parameter s, evaluated for one sequence of 16 frames of the heart beat. The remaining parameters has set to $h = 15$, $r = 10$, $g = 10$, $q = 1$, $a = 5$ and $\sigma = 1$. The first frame has been selected as template and has been chosen as the mid time between the end systolic and end diastolic frames. This experiment evaluates how searching window impacts MCE registration.

The third experiment was designed in order to evaluate the registration limitations for rotations angles and its behaviour with different s parameter, as shows in Fig. 3. The remain parameters has been fixed as in the previous experiment. As the fourth experiment, illustrated in Fig. 4, the result for q entropic parameter changing has been tested for 10 and 15 rotation degrees of the images to be registered. The registration parameters keep values as above, except $r = 30$ and the $s = 15$.

4. Discussion and conclusions

First experiment has shown that choices in histogram bin size plays an important role in MCE registration, with a greater impact for DE and MI when compared to NCC. When histogram size h is low, it becomes less sparse improving statistics. The best result in this case was found

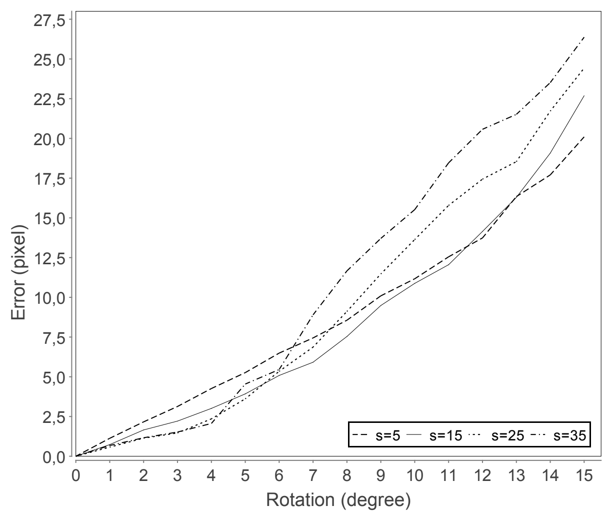

Figure 3. Registration error as a function of simulated rotations angles applied to the images, plotted for some values of searching window size s.

for DE for $h = 15$, although MI has also been improved for this number of bins. The MI calculation employs a joint histogram (2D), which could be very sparse for small region images, as is this case. Images similarity is evaluated within small searching windows, up to 81×81 pixels, and it is still too small for MI to work. Furthermore, this is the reason the MI results becomes better as the s increases. However, there is a limit where estimated error is augmented again. Above this value, the searching window turns to large and local information is lost. This is the same for DE and NCC. As DE is evaluated only applying on 1D histogram, the limitation caused by sparsity is less than in MI, so the DE reaches low s values with more accuracy. At very low s values, there is not enough points to be sampled, therefore, there is a lower size limit. The DE shows its better results for $s = 20$ approximately.

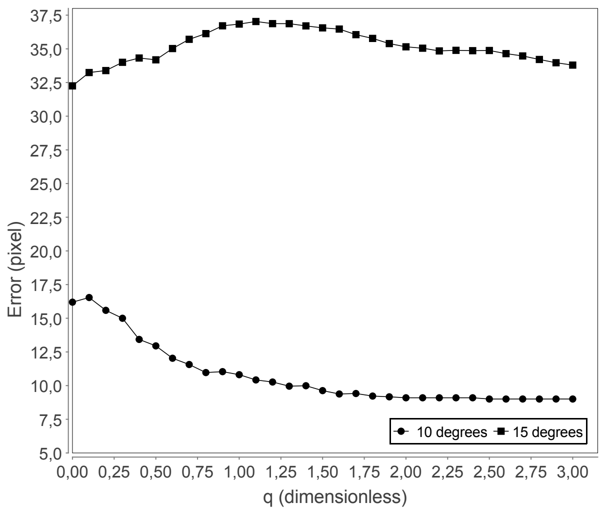

Figure 4. Registration error as a function of entropic parameter q for two different rotation degrees.

The experiment two shows that DE is suitable for sequential frames registration. Again, there is a best value for s, within the interval $[15, 20]$ and the error presents a relative low oscillation through the sequence. The crucial method limitation is on image rotation, which makes more difficult regions matching procedure as the regions undergoes rotation and searching window does not. The experiment three has show that there is a threshold value for MCE, approximately 10 degrees of rotation, determined by visual inspection. Above it, registration does not work well. In the fourth experiment, the generalized entropy parameter q (1) has shown influence the error. For 10 rotation degrees, as q raises the registration becomes better, however, exceeding the rotations limits, increasing q does not improve registration. Although q can improve accuracy, there is not an expressive difference in error by increasing q. q values about 1 or 2 have shown best results.

Three similarity metrics have been tested for sequential MCE images registration to a reference image. DE has shown the best result compared to NCC and MI, for suitable choice of image histogram bin size. Histogram size has shown influence significantly DE and MI similarity metrics, unlike NCC that shows little impact from h. With all other parameters fixed and histogram size, the searching window has been changed and its influence in registration verified. The s parameter controls how much local or global aspects of registration takes place and, as s raises, the registration scale changes from local to global. Although the region matching approach for registration imposes some restriction for rotation, the procedure has worked for up to 10 rotation degrees. As the MCE registered frames did not presents relative rotation degrees grater than 10 and displacements grater than 20 pixels, the method has worked successful for MCE image sequence. The smoothing in displacement field procedure also has shown a significant effect in registration, as it turns the displacements more smooth, allowing local or global registration control and correcting some possible erroneous calculated displacements. The method can also be applied iteratively, which the image undergoes sequential small corrections until successful registration is achieved.

Acknowledgements

The authors would like to thank CAPES and FAPESP (grant 2006/00723-9) for financial support.

References

[1] Murta LO, Pazin-Filho A, Schmidt A, Almeida-Filho O, Marin-Neto JA, Maciel BC. Segmental quantitative analysis of myocardial contrast echocardiography images using a bullseye representation. Computers in Cardiology 2003 Sept. 2003;177–180. ISSN 0276-6547.

[2] Buzug TM, Weese J, Fassnacht C, Lorenz C. Image registration: Convex weighting functions for histogram-based similarity measures. 1997; 203–212.

[3] Penney G, Weese J, Little J, Desmedt P, Hill D, hawkes D. A comparison of similarity measures for use in 2-d-3-d medical image registration. Medical Imaging IEEE Transactions on Aug. 1998;17(4):586–595. ISSN 0278-0062.

[4] Wand MP. Data-based choice of histogram bin width. The American Statistician 1997;51(1):59–64.

[5] Boon JP, Tsallis C. Special issue overview Nonextensive statistical mechanics: new trends, new perspectives. Europhysics News November 2005;36:185–186.

[6] Unser M. Splines: a perfect fit for signal and image processing. Signal Processing Magazine IEEE Nov 1999;16(6):22–38. ISSN 1053-5888.

Address for correspondence:

Luiz Otávio Murta Junior
Departamento de Física e Matemática - FFCLRP - USP
Av. Bandeirantes, 3900. CEP 14040-901 - SP. Brazil
murta@ffclrp.usp.br