IMAGE REGISTRATION AND ITS RELEVANCE IN PLANTAR PRESSURE IMAGES

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Abstract

In this monograph, common methodologies of image registration are described. Only some of them are referred since the main objective is not to give an extensive report about all registration methodologies but describe some of the most used and provide some examples of works where different registration techniques are explored.

Basically, there are some common steps in image registration: selection of the type of features to use (image segmentation can occur), establishment of a similarity measure, choice of the geometric transformation, optimization procedure and an interpolation to map intensity levels at the new positions. Additionally, pre-registration methodologies can be applied to speed up the optimization algorithm. Usually, a matching procedure is also needed in feature based registration. There are many applications of image registration; the most important for this work is the alignment of pedobarographic (i.e. plantar pressure) images.

After an introduction, the classification of image registration methodologies is achieved in this monograph. The distinction between features based and intensity based registration methodologies is addressed. Afterwards, some transformations are described as well as some similarity measures used. Examples of optimization algorithms are pointed and then the interpolation step is also referred. Some accuracy measures are also pointed. Finally, some of the most important works using image registration methodologies are mentioned with emphasis in plantar pressure images registration. In this domain, the spatio-temporal alignment of pedobarographic images is considered as very promising due to its potential relevance in clinical context.
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1. Introduction

Image registration is commonly referred as the process of aligning two images or even temporal sequences of images on a common spatial coordinate system. There are many fields where image registration can be useful but here the main interest is the medical area. Some of the most important applications in this area are the combination of data from images of same modality or different modalities; the search for differences in size and shape over a time range; the application on image-guided surgery and the comparison between image from a patient and an image database or atlas (Hajnal et al., 2001).

Nowadays, several imaging techniques are available in the medical area, and a patient often performs more than one exam to monitor or detect health problems. These exams can be from the same modality or from different modalities. Sometimes the image analysis is very difficult to the physician and it depends greatly on his experience to mentally combine data from different images. Image registration is an important help because it allows finding common shapes and structures between images and establish temporal correspondences that facilitate complex tasks of image analysis. Image registration can also be useful in plantar pressure images. These images are acquired with different step frequencies and positions because every person has a personal gait. The registration allows finding correspondences between plantar pressure images and integrating their data in a meaningful way facilitating the diagnosis.

In the registration process the inputs are a pair of images and the output is a geometrical transformation that maps points from one image to another image. It is important to distinguish between registration and fusion. Fusion is a process after registration where the data of involved images is combined. This combination may be performed intuitively by physician or by a way in which important aspects are highlighted (e. g. the tumor growth can be highlighted with different colours for different overlapped images in order to distinguish size differences over time). Frequently, registration is also referred as alignment. A previous distinction has to be made: there are registration methodologies based on image pixel intensities (also known as area-based methods) and based in features in the images. The first step after any registration process is to analyse data from all images in order to choose the best approach to use in the registration. If images have no distinctive landmarks or even
shapes, lines or another prominent characteristic extracted by a segmentation methodology, i.e. features, and most important information is based on pixel intensity distribution, a pixel intensity based methodology is the most suitable methodology to use. If there are landmarks or segmented structures with more importance than pixel-intensity distribution, a feature-based registration methodology is the appropriate path to follow. The detected features must have common characteristics in all images whose correspondence will be found using their spatial relations or feature descriptors (Zitová and Flusser, 2003).

Segmentation techniques should be used to detect image features as edges, contours, corners, curves and points of intersection. After features detection, distinctive points of that features have to be assigned. These points are commonly referred as control points (CPs) and may be centroids, line endings, etc.

Usually the registration process consists in some common steps: selection of the type of features to use (pixel intensities, landmarks or segmented structures) in which a process of segmentation can occur (usually in feature based methods only); establishment of a similarity measure; choice of the geometric transformation; optimization procedure and an interpolation to map intensity levels at the new positions. These steps are described in more detail in the following sections. A pre-registration methodology can also be used to estimate an initial transformation. Thus, the convergence speed of optimization algorithm may be improved in post-registration. Frequently, a rigid geometric transformation is pre-registration due to its simplicity (Oliveira and Tavares, 2012b). An interpolation method is also normally required because remapping of pixel intensities is needed after transformation. The accuracy evaluation is very important at the end of any registration procedure as results need to be validated.
2. Image registration classification and usual methodologies

2.1 Classification

Registration methods may be divided according to different criteria. Maintz and Viergever (1998) suggested a classification based on nine subdivided criterions. Later, this classification was used and reduced to eight categories by Fitzpatrick et al. (2000):

**Dimensionality**

Usually medical images are in three-dimensional (3D) space, but sometimes they are bi-dimensional (2D). Additionally, it is possible to consider time as a dimension in temporal sequences of images. Most common registration methods are classified as 2D/2D, 2D/3D, 3D/3D and 4D/4D.

**Registration basis**

This criterion considers the nature of the features used in the registration procedure. These features may be intrinsic or extrinsic relatively to the patient data. Extrinsic features are added to the patient facilitating their visualization by any imaging modality. As result, registration of acquired images is faster and less complex (Maintz and Viergever, 1998). Extrinsic features may be invasive or non-invasive (less accurate). In turn, intrinsic methods use only patient internal data as landmarks (anatomical or geometrical characteristics extracted from images), segmented structures (e.g. points, curves, surfaces) or features obtained from voxel properties.

**Geometrical transformation**

Classification of registration techniques can also be made according with the mathematical method used to map points from an image to another one. If lines are mapped onto lines, a projective transformation is occurring; when parallel lines are mapped onto parallel lines, it is considered affine transformation; if only rotations and translations are allowed (dimensions and angles are unaltered), then it is called rigid transformation, and if lines are mapped to curves, an elastic or curved transformation is used.

The domain of the transformation is also classified as global if all image data is used and local if only particular image features are used.
Degree of interaction

The registration algorithm may be automatic, semi-automatic or interactive relatively to the user interaction. Ideally, the automatic procedure is preferable and many researchers have been developing automatic algorithms. Sometimes human interaction is desired because speed and accuracy may be increased.

Optimization procedure

The parameters used in the transformation can be found by direct computing or by maximizing or minimizing a function to iteratively find the optimum.

Modalities

Registration can be found in monomodal (images only from same modality), multimodal (images from different modalities), modality to model (registration is performed between an image and a model) or patient to modality (registration is performed between an image and the patient himself) applications.

Subject

Images may be from the same patient (intrasubject), from different patients (intersubject) or from a patient and a database built from many patients (usually referred as atlas).

Object

Categorization is also made according with the anatomic region involved in the registration procedure. Head (Ashburner, 2007; Christensen et al., 1994, Shen, 2007; Zao et al., 2004) and pelvis (Shen, 2007) are some examples frequently found in literature.

2.2 Transformation models

Estimation of the mapping function consists on finding the most suitable function to the problem and estimating its parameters. In 1D, this mapping function is conceptually described as:

\[ T: x \mapsto x' \iff x' = T(x) \]  \hspace{1cm} (1)
where transformation \((T)\) maps \(x\) to \(x'\). Obviously, this mapping function has to be chosen taking some features into account, like images dimensionality (2D/2D, 2D/3D, 3D/3D), pretended accuracy and computing speed.

Several mapping functions have been studied over the last years. Some of those functions are presented in this work (an overview is depicted in Figure 1).

If 2D pixel coordinates are converted to homogeneous coordinates, a generic transformation in matrix form can be represented as:

\[
\begin{bmatrix}
x' \\
y' \\
w
\end{bmatrix} = \begin{bmatrix}
a_{11} & a_{12} & t_x \\
a_{21} & a_{22} & t_y \\
a_{31} & a_{32} & 1
\end{bmatrix} \begin{bmatrix}
x \\
y \\
1
\end{bmatrix} \tag{2}
\]

In this equation (2), parameters \(a_{11}, a_{12}, a_{21}\) and \(a_{22}\) are representing deformations, \(t_x\) and \(t_y\) are representing translations, \(a_{31}\) and \(a_{32}\) give the projection point, \(w\) is a dependent parameter used to normalize pixel coordinates, and \(a_{31}\) and \(a_{32}\) are only different of zero to the projective transform. Thus, \(w\) will be 1 (one) to affine, similarity and rigid transformations. This transformation matrix is applied in projective transform and its subsets (affine, similarity and rigid).

2.2.1 Projective transform

This mapping function is useful to relate 3D anatomy with 2D images acquired from a patient (Fitzpatrick, 2000). Its representation in 2D space is given by:

\[
x' = \frac{a_{11}x + a_{12}y + t_x}{a_{31}x + a_{32}y + 1} \tag{3}
\]

\[
y' = \frac{a_{21}x + a_{22}y + t_y}{a_{31}x + a_{32}y + 1} \tag{4}
\]

In this approach, rotation, scale, shear, translation and perspective projection (conferred by non-zero values of \(a_{31}\) and \(a_{32}\)) are transformed. The straightness of lines is kept. At least, four corresponding points are needed in both images.
2.2.2 Affine transform

Usually, it is applied to global models, in which the transform is valid to all image area, and can be represented in 2D as:

\[ x' = a_{11}x + a_{12}y + t_x \tag{5} \]
\[ y' = a_{21}x + a_{22}y + t_y \tag{6} \]

In these equations, \( a_{31}, a_{32} \) (from equation 2) are set to 0 (zero).

This transform keeps straightness of lines and their parallelism, but it may change the angles between them (Fitzpatrick, 2000). In this transform, a minimum of three non-collinear corresponding points is needed between both images.

2.2.3 Similarity transform

This transform is a sub-case of affine transform. Usually, it is applied globally, and can be represented in 2D space as:

\[ x' = s[x\cos(\theta) - y\sin(\theta)] + t_x \tag{7} \]
\[ y' = s[x\sin(\theta) + y\cos(\theta)] + t_y \tag{8} \]

As can be observed in these equations, this transform only performs scaling, rotation and translation. Thus, angles and curvatures are preserved. This mapping transform needs a minimum of two control points from both images (Zitová and Flusser, 2003). As obvious, if more corresponding points are used, the accuracy can be raised and the computing time can be reduced.

2.2.4 Rigid transform

This transform (also known as Euclidian transform) is a subset of the similarity transform. In 2D space, it is defined as:

\[ x' = x\cos(\theta) - y\sin(\theta) + t_x \tag{9} \]
\[ y' = x\sin(\theta) + y\cos(\theta) + t_y \tag{10} \]
In this approach, angles between lines, length between points and areas are held; only rotation and translation occur. This transform is computed from a minimum of two corresponding points in both images. Rigid transform is preferentially used in registration of rigid structures and in the pre-registration step as initial approximation (Oliveira and Tavares, 2012).

2.2.5 Curved transform

In fact, it is reasonable to say that this transform, also known as elastic or deformable, is more adequate for most studies related with medical images because deformations in almost all structures of the body are possible. Some of the most used transformations in last years have been based on splines. Generally, in splines-based methods, after finding the corresponding points from both images, the target and the source images, a spline is used to establish correspondences. Spline-based methods may interpolate or approximate the displacement of the corresponding points allowing to map their locations in the target image.

Figure 1 Representation of 2D geometric transformations applied to an "Original" square.
Some of the most popular splines are the thin plate splines (Roehr et al., 2001) and the B-splines (Mattes et al., 2003; Oliveira and Tavares, 2012b; Rueckert et al., 1999).

2.2.5.1 Thin Plate Splines (TPS)

This is a global transformation, because if a corresponding point is changed, all other points are also changed (Crum et al., 2004; Oliveira and Tavares, 2012). It belongs to the radial basis functions family. TPS interpolation is represented as:

$$x' = a_{11} + a_{12} + t_x + \sum_{i=1}^{N} F_i r_i^2 \log (r_i)$$  \hspace{1cm} (11)

In this equation, $r_i$ represents the Euclidian distance ($|x-x_i|$), where $x$ is an interpolated point and $x_i$ is a corresponding point (control point). This TPS interpolation minimizes the bending energy (Holden, 2008; Mitra et al., 2010).

2.2.5.2 B(asis)-Splines

Methods based on B-Splines are considered of the type free-form deformation (FFD) as they deform an object by changing a mesh of control points. Thus, B-splines based transformations may be considered as local transformations. The number of degrees of freedom and the consequent computational cost are highly dependent of the control point mesh dimensions (Rueckert et al., 1999). Generically, a B-Spline can be defined as:

$$Q(x) = \sum_{j=0}^{n} P_j B_{j,d}(x), \quad t_{d-1} \leq x \leq t_{n+1}, \quad n \geq d$$  \hspace{1cm} (12)

where $P_j$ is a control point and $j$ is its index, $n + 1$ is the number of control points, $d$ is the number of control points controlling the segment and $d – 1$ is the B-Spline degree (e. g. a cubic Spline ($d = 4$) uses 4 control points), finally, $t_j$ is the knot value.

Usually, in image registration, uniform B-splines are chosen (Oliveira and Tavares, 2012b). In this approach, the knots are equally spaced, and the following condition has to be verified:

$$t_{j+1} = t_j + k$$  \hspace{1cm} (13)
where \( k \) is a constant scalar value.

Bsplines of degree 1 (one), or linear B-Spline, performs linear interpolation and is very popular due to the low complexity required. When B-Splines degree is larger than one, there is no linear interpolation (Thevenaz et al., 2000). Instead, they perform approximations, providing a smooth function, and an error metric has to be minimized by an optimization method (Holden, 2007).

In uniform cubic B-Splines, \( B_{j,\beta}(x) \) is the \( j \)th basis function such that:

\[
B_0(x) = \frac{1-x^3}{6} \quad (14)
\]
\[
B_1(x) = \frac{3x^3-6x^2+4}{6} \quad (15)
\]
\[
B_3(x) = \frac{-3x^3+3x^2+3x+1}{6} \quad (16)
\]
\[
B_4(x) = \frac{x^3}{6} \quad (17)
\]

### 2.3 Similarity measures

Similarity measures assess how much two images match. There are similarity measures more suitable for intensity-based registration methods, more appropriate for feature-based registration methods or even for both classes of registration methods.

A similarity measure based on pixel intensity differences is the sum of squared differences (SSD) or the normalized sum of squared differences that is given by:

\[
SSD = \frac{1}{N} \sum_{x=1}^{N} [A(x) - B(T(x))]^2 
\]

where \( N \) is the number of pixels of all the image, or just from a region of interest of the image, \( A(x) \) is the intensity of image \( A \) in position \( x \) and \( B(T(x)) \) is the intensity of corresponding point in image \( B \) estimated by the transformation \( T(x) \). This is a similarity measure widely used in intensity-based methods and assumes that the corresponding points should have similar intensities (Oliveira and Tavares, 2012a). This assumption has a drawback: SSD measure is very sensitive to the Gaussian noise, i.e. to pixels with large intensity differences. The optimum is achieved to the minimum value of SSD. As this method assumes approximate intensity values between the same
structures, it is only adequate for monomodal registration. In order to minimize the sensitivity to the Gaussian noise, the sum of absolute differences (SAD) may be used:

\[
SAD = \frac{1}{N} \sum_{x=1}^{N} [A(x) - B(T(x))] \quad (19)
\]

In a study of Hoh et al. (1999), SAD is compared against another similarity measure, the stochastic sign change – SSC, applied in the rigid registration of PET images.

Another similarity measure widely used in intensity-based registration methods is the cross-correlation (CC):

\[
CC = \frac{\sum_{x=1}^{N} (A(x) - \bar{A})(B(T(x)) - \bar{B})}{\sqrt{\sum_{x=1}^{N} (A(x) - \bar{A})^2 \cdot \sum_{x=1}^{N} (B(T(x)) - \bar{B})^2}} \quad (20)
\]

where \(N, A(x)\) and \(B(T(x))\) are the same parameters defined for SSD, and \(\bar{A}\) and \(\bar{B}\) are the mean of all intensities in the pixels of image \(A\) and \(B\) used, respectively. In this approach, corresponding pixels have a linear intensity relationship; as such, it is more adequate for monomodal registration. A high cross-correlation is desirable with the aim of finding the optimum.

Mutual information (MI) has been an extensively used similarity measure in the last years. It is based in information theory and reveals how much information an image contains about a second one (Oliveira and Tavares, 2012a; Rueckert et al., 1999). This measure considers probabilistic relationships between intensities, and its value is obtained from entropies of intensity distribution:

\[
MI = H_A + H_B - H_{AB} \quad (21)
\]

where \(H_A\) and \(H_B\) represent the Shannon’s entropy of the pixels in image \(A\) and \(B\), respectively, and \(H_{AB}\) represents their joint entropy, which is achieved by a joint histogram. These entropies are obtained by:

\[
H_A = -\sum_{i=1}^{N} P_i \log P_i \quad (22)
\]
where $P_i$ and $P_j$ are the probability of intensity $i$ appears in target image and the probability of intensity $j$ appears in source image, respectively, and $P_{ij}$ is the joint probability of both intensities occurring at the same position. The MI has a maximum if the images are correctly aligned.

The normalized mutual information (NMI) model was developed to minimize the overlap problem of MI (Studholme et al., 1999):

$$
NMI = \frac{H_A + H_B}{H_{AB}}
$$

Unlike SSD and CC, MI-based methods are proper for multimodality registration since there are no direct relations between intensities. MI may also be used in monomodality registration.

### 2.4 Optimization process

The optimization procedure changes the parameters from the transformation model in order to maximize/minimize the similarity measure. This is an iterative approach where the initial transformation is gradually improved until there is no possibility to obtain a better value to the similarity measure. One of the greatest challenges in image registration is to avoid local optimums because optimization algorithms may converge to non-global optimums which lead to incorrect registration results. A common approach to minimize this problem is the multiresolution scheme. In this scheme, images are registered at low resolution and the transformation obtained is used as starting approach for a next registration at higher resolution. This is a hierarchical approach. In order to obtain the low resolution images, a low-pass filter can be used to smooth large peaks of intensity. Thus, the multiresolution scheme allows a faster convergence, and it decreases the probability of converging to local optimums.
One of the most used optimization methods is the iterative closest point (ICP) (Besl and McKay, 1992). This method is useful in matching optimization since matching and geometric transformation are simultaneously sought in feature-based methods (Oliveira and Tavares, 2012a). Matching is a needed step in feature-based methods in order to establish correspondences between features extracted from the images to be registered. Therefore, these features are aligned in image registration procedure. ICP is an algorithm which iteratively searches for the minimum distance between pairs of control points. Usually, transformation parameters are estimated by iterations until a stopping criterion. As a conceptual example, it can be considered a surface with a set of points \( p_j \) and a model surface \( X \) in another image. ICP algorithm will iteratively search for the minimum value of:

\[
d(p_j, X) = \min(||x - p_j||)
\]

(26)

where \( d \) is the distance between \( p_j \) and the closest point \( x \) in the model surface.

Other optimization methods used to maximize or minimize a similarity measure have been widely used in the last years. Some of these methods are Powell’s Method, Downhill Simplex Method, Steepest Gradient Descent and the Conjugate Gradient Method. These methods are well detailed in Press et al. (2007).

2.5 Interpolation process

The interpolation process arises from the necessity of finding new intensity values of pixels when they are mapped by a transformation. Frequently, nearest neighbour or bilinear interpolation are satisfactory methods. However, more accurate methods may be necessary. Usually, there is a convolution between the image and an interpolator kernel. Some of the other interpolator kernels are: quadratic splines, cubic B-Splines, Gaussians, and truncated sinc functions as sinc functions have infinite extent. The nearest neighbour interpolator basically assigns the nearest pixel intensity value to the pixel being interpolated. Frequently, the nearest neighbour interpolator is avoided because the high probability of artifacts occurrence in the resultant image. The choice for an adequate method is highly dependent of the desired trade-off between accuracy and computational cost. A review of some interpolation methods is performed in Thévenaz et al. (2000). In Lehmann et al. (1999) several interpolation methods are
compared in terms of space and Fourier analysis and their computational costs and interpolation errors are evaluated.

2.6 Accuracy evaluation

Image registration methodologies need to be evaluated according with their accuracy. Typically, accuracy is not easy to assess because errors may be hidden during the registration process or even undistinguishable from natural differences of the input images. There are three typical errors which can affect final result: localization error (due to inaccurate detection of CPs); matching error (resulting from false matches in potential correspondences between CPs) and alignment error (due to wrong choices in transformation model or its parameters). Many approaches to evaluate accuracy are used and many others are under development. Obviously, the simplest one is the visual evaluation by an expert. The mean square error (MSE), a statistical measure, may be applied to the CPs to assess the alignment error between them. However, this method is not adequate to this application because of the over-fitting (Zitová and Flusser, 2003). Another method consists on using target registration error (TRE) which is the displacement between a pair of CPs after registration. TRE is given by:

\[ TRE = a - T(b) \]  

(27)

where \( a \) is a point from image \( A \) and \( T(b) \) is the corresponding point in image \( B \) after transformation. Those points should have some anatomical significance.

Fiducial registration error (FRE) is another possible measure for registration errors. Fiducial points are reliable corresponding point pairs for registration purposes. In order to determine fiducial points within a distinct feature (fiducial feature), a fiducial localization is needed. The error resulting from incorrect fiducial localization is known as fiducial localization error (FLE). The fiducial registration error (FRE) quantifies the misalignment caused by FLE when fiducial points are aligned in the registration process. FRE is given by:

\[ FRE = a_i - T(b_i) \]  

(28)
where $a_i$ is a point from the fiducial feature $i$ in image $A$ and $T(b_i)$ is the corresponding point from the same fiducial feature in image $B$ after transformation.

The difference between FRE and TRE is that in TRE corresponding points with clinical or anatomical relevance are used, while FRE uses corresponding points from easily visible structures that can have clinical interest or not. The clinical relevance of TRE is an advantage of this measure. Both TRE and FRE are applied only in rigid registration methodologies (Fitzpatrick et al., 1998). Frequently, FRE is also represented as a root mean square of the distance between corresponding points:

$$FRE = \sqrt{\frac{\sum_{i=1}^{N} (a_i - T(b_i))^2 w_i}{N}}$$

(29)

where $N$ is the total number of fiducial features and $w_i$ is an optional weighting factor used to give different influences to each fiducial feature $i$ in the total measurement of FRE. The weighting factor is useful because fiducial features may not be equally reliable.

Another approach is to compare the results from an image registration method under evaluation and a gold-standard method. If no gold-standard method exists, the comparison has to be made with a different method and if the results are similar there is a high probability of good accuracy (it is a qualitative measure). A consistency test is also used and consists on the assumption that rigid registration from image $A$ to $B$ produces the same results when the same transformation model is applied from $B$ to $A$ (Crum et al., 2004).

### 2.7 Main applications of image registration techniques

Currently, many imaging techniques are available. Some of the most used are: X-ray, computed tomography (CT), computed tomography angiography (CTA), magnetic resonance imaging (MRI), magnetic resonance angiography (MRA), ultrasound (US), single-photon emission computed tomography (SPECT), positron emission tomography (PET).

There are several articles focused in head images registration since this anatomical structure can be considered as a rigid element, mainly due to the rigid registration simplicity comparing with non-rigid registration methodologies. However, in the last
years, non-rigid methods have been increasingly explored. One of the most prominent applications of non-rigid registration is on the organs motion. The spatio-temporal behaviour may be important to the diagnosis and image registration methodologies can assume an important role in finding correspondences in time. In Shen et al. (2005) a non-rigid methodology is proposed in order to estimate cardiac motion from a sequence of MR images. A morphological signature for each point is used with the aim of minimizing potential errors in matching and deformable registration procedures.

Lung is another important organ regarding its deformation during respiratory motion. In this case, all surrounding structures may be affected by this motion. Spatio-temporal analysis may also be useful when a physician is looking for pathologies propagation or even organs degradation. In addition, radiotherapy and cancer monitoring is one of the most interesting areas of investigation in image registration due to spatio-temporal changes. As obvious, the input images may have temporal differences with large variations. If the cardiac cycle monitoring needs some images in a few seconds, the tumour progression may be characterized by images with a difference of months or even years. Another potential use of image registration techniques is in surgery report; i.e., comparing organs before and after surgery.

A very common requirement in medical area is to integrate the data from various imaging techniques. Images from different imaging techniques may have different field of view, resolution and slice orientation (Hill et al., 2001). Actually, in order to perform some pathology diagnosis or even to search for some health problem, some imaging modalities may be simultaneously required. Thus, there is a strong need by data fusion to help diagnosis. An evident case is PET-CT fusion because these modalities are frequently required to the same diagnosis. In most cases, more than one modality is required due to the data complementarily between them.

Deformable registration could be especially important in intersubject registration. The most evident example is the neurosurgery area. There are many databases with brain images from individuals with neurodegenerative diseases. The registration is particularly useful to combine data from several brains (with and without disease) with the aim of finding common steps in disease evolution and even to predict potential brain problems.

Another important application of image registration is in image guided surgery where it is needed an alignment between images and the patient in surgery position.
This kind of alignment is also needed in radiation therapy. A commonly used methodology is the registration based in external markers. If external markers are placed in the body (usually attached to the skin), matching between images could be accurately performed. So if any pathological perturbation occurs, registration can continue to be made accurately. However, any displacement in markers position during image acquisition can cause bad results. Additionally, if an organ such as heart varies its position during cardiac cycle, the accuracy is compromised (Mäkelä et al., 2002). In Papavasileiou et al. (2001) SPECT-SPECT image registration is performed based on external markers filled with Technetium-99m in a radionuclide therapy.

Hybrid approaches are frequently used as well. In these approaches, feature-based method and intensity-based methods may be used in the same registration procedure (Liao et al., 2011; Oliveira and Tavares, 2011).
3. Pedobarographic image registration

First of all, it is important to define that pressure is the force divided by the contact area, where force quantifies the interaction between the foot and the floor in this case.

Plantar pressure measurements may provide important information about human walking and some associated health problems. A plantar pressure image can be seen in Figure 2. It is hard to define “abnormal” gait since every person has a personal gait pattern. However, using “control groups” may be a good solution to identify clear gait disturbances. Diabetic peripheral neuropathy (DPN) is an example of a disease influencing human walking since the disease causes many problems in feet due to the progressive degeneration of the peripheral nerves (Bacarin et al., 2009). Many authors have been trying to find relations between diabetes (with consequent feet ulceration) and the plantar pressure in patients (Bacarin et al., 2009; Caselli et al., 2002; Ownings et al., 2009; Payne et al. 2001; Veves et al., 1992; Waldecker, 2012).

Although there is controversy surrounding the real clinical applications of plantar pressure measurements, Rosenbaum and Becker (1997) agree with Hughes (1993) concerning the main applications: the assessment of treatment by pre and post operative comparisons, longitudinal evaluation of patients in order to control treatment therapies or monitoring disease progression and the control of orthotic interventions effectiveness.

Gait analysis by pressure measurements can provide data to help in treatment options analysis and distinguish disturbances.

Sensor materials used to measure pressure are described in Rosenbaum and Becker (1997).

The biomechanical characteristics of human walking are investigated in Pataky et al. (2008a). In this study, a relation between human walking speed and plantar peak pressure is established. It is found that midfoot and proximal forefoot peak plantar pressures have a negative correlation with walking speed, and it is suggested that subsampling methods to acquire plantar pressure measurements are unsuitable comparing with pixel level acquirement methods. As Pataky et al. (2008a), much investigation has been performed in order to study plantar pressure measurements during human walking (Burnfield et al., 2004; Morag and Cavanagh, 1999; Rosenbaum et al., 1994; Segal et al., 2004).
Harrisson and Hillard (2000) accomplished a study in plantar pressure images registration. In this study, a temporal sequence of images is aligned by a principal axis transformation method. A different approach is performed in Bastos and Tavares (2004) and Pinho and Tavares (2004). In this approach, a finite elements modelling technique is applied and after a modal matching method is used.

Later, in Pataky et al. (2008b), seven different rigid-body methods for intrasubject plantar pressure image registration are compared.

![Figure 2 An example of a plantar pressure image. Here, white points (or pixels) represent high pressure pixels and black points suggest no contact between foot and the surface of the equipment.](image)

The work of Oliveira et al. (2009a) presents a registration technique where feet contours are segmented and then contour points are matched between images. In Oliveira et al. (2009b) only points from contours with high affinity are considered in order to avoid wrong matches between points without correspondence. A registration of pedobarographic images in the frequency domain is realized in Oliveira et al. (2010). Cross correlation and phase correlation are the registration methodologies used in this domain. The major claim in this work is the near-real time potentiality of this algorithm due to its computational speed, accuracy and robustness. In another work of Oliveira and Tavares (2012c), five different registration methodologies are compared in terms of accuracy, robustness and computational speed.
Oliveira et al. (2012d) developed a shape recognition algorithm using a cross-correlation alignment method in order to distinguish the left and the right foot. Additionally, arch index and modified arch index are automatically measured.

All works previously referred are performing pedobarographic image registration only in static images. However, innovative works in spatio-temporal image registration have recently been made. In Oliveira and Tavares (2011), two alignment types are performed: a spatial alignment using geometric transformation models and temporal alignment using polynomial functions up to 4th degree. In a more recent study (Oliveira and Tavares, 2012b), B-Splines are used and show better accuracy than polynomial functions referred in previous work.
4. Conclusions

The spatio-temporal alignment is a promising development area since there are very few solutions in this field, and the data resulting from such alignment can provide important tools to the medical diagnosis.

In any area, if there are more measurements, more reliable may be the result. In human walking, step sequences mostly vary in overall speed of walking and even between steps in the same sequence. The same step frequency cannot be reproduced among different clinical trials even if the individual tries to. In plantar pressure measurements three to five walking trials are advised in order to improve results reliability (Hughes et al., 1991). In this context, a mean image sequence could be a potential application of spatio-temporal alignments in pedobarographic images (Oliveira et al., 2011) since it allows to obtain a more reliable sample. Obviously, it is always important to achieve the best accuracy, robustness and computational speed. Frequently, a trade-off between accuracy and computational speed is needed. Ideally, any approach of a potential software to provide a diagnosis tool would be reliable in real-time. Taking these facts into account, there is considerable work to do in spatio-temporal registration.

In this Thesis, the work of Oliveira and Tavares (2012b) will be continued. Better solutions will be sought in order to improve the accuracy, the computational speed or even the robustness. Any stage of the existing algorithms could be changed but initially, the best approach is looking for better pre-registration methodologies since pre-registration has large influence in overall registration results (Oliveira and Tavares, 2012a). Thus, in further work, a comparison between various initial approximation methodologies will be made. Not only all methodologies described in this monograph would be used, but also other techniques would be explored.

The main resources needed in this Thesis are the plantar pressure images, a development environment supporting C++ language and algorithms from Oliveira and Tavares (2012b) work. Images are acquired from Oliveira and Tavares (2012b). These images contain plantar pressure data from individuals walking. There are images from twenty six individuals acquired using an EMED system (Novel GmbH, Germany). Microsoft Visual Studio 2010 will be the development environment in this work since libraries compatibility with acquired algorithms is guaranteed.
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