INTRODUCING TENSOR ANALYSIS FOR BIOMEDICAL IMAGE REGISTRATION

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Abstract. *Physiological medical image examinations consider as first step on the analysis how to track the same point of the patient body during some time; this procedure is named "Image Registration". In this work, two approaches to define how identify same anatomical point to be follow in a series of patient images during a dynamic infrared images examination are presented allowing study temperature variation of each point. One of these, use a never before considered methodology in the area: how tensor is transformed when there is coordinate modifications. This approach can be implemented in a semi-automatic method for image registration on Region of Interest (ROI) pre-processing without error when is possible to consider that the displacements of the volunteer are translation and rotation along the time of the examination. If there is other more generic motions, the obtained point coordinates of the captured frames can be considered as a first step and additional correction is required for a perfect description of the bijective transformation of points along the examination time interval.*

Keywords: Infrared Images, Image Registration; Dynamic Thermography, Computer Aided Diagnostic Systems.

1. INTRODUCTION

The temperature distribution on the human skin can be measured by using infrared cameras and are named thermal image. These images present a symmetric pattern regarding the sagital plane. Variations of this symmetry during the examination time can constitute a signal of abnormality. Thermal imaging is a low cost, fast, non-contact and non-invasive examination that had been applied in many medical applications for finding inflammations, localized pains, peripheral vascular diseases, and some types of cancers. Malignant tumors cause increase growing of cells with tissue invasion. For growing these tumors requires more nutrients than growing normal cells, this causes the development of new blood vessels in the region and more activation of the peripherical immune system (which provides a mechanism for the body to neutralize or destroy the abnormal cells by using specialized proteins, lymph channels and nodes). In order to maintain homeostasis in a safe range of substances there is an increased fluid flow in the tumors area, and it presents differential behavior related to the heat transfer that can be used to aid in the identification of malignant tumors (Borchartt et al. 2013). Tracking a point to construct its temporal series during an examination becomes problem because of the inevitable involuntary patient movement that appears at same time the natural variation in body temperature. In order to correctly represent the same anatomic points of the patient body, in a sequence of image acquisition during the time of an infrared acquisition, the calculation of the *bijective transformation (i.e. the* inversive function) between frames (or at least in the relevant region that is called as Regions of Interest, ROI) is fundamental, because this allows identification of same points and the extraction of the knowledge of their behavior during the observation (Silva et al, 2015). Such a correspondence in image processing applications is called *Image Registration* (Zargochev and Goshtasby, 2006), (Yong and Robert, 2017), (Zhang et al.. 2017). In this work, we propose a new approach for compute such bijective transformation that have been shown to be quite adequate for examinations of the thyroid region.

2. DYNAMIC INFRARED TERMOGRAPHY

More recent applications of thermography in medicine, mainly in breast cancer diagnosis, have shown the effectiveness of Dynamic Infrared Termography (DIT) in image analysis (Silva et al. 2014). In the DIT protocol for thyroid examination, initially, the patients must be in front of the camera, sitting (with the head on a head support in order to minimize the possible displacements), with the head tilted slightly back and the patient looking up (González et al, 2017). In order to monitor the dynamic response of the skin temperature, after thermal stress (i.e application of forced ventilation using a fan), a series of images is captured (by a FLIR thermal camera model SC620 with sensitivity of 0.04^0C and resolution of 640x480 pixels) for 5 minutes producing a sequence of 20 images. One of these images can be seen in Fig. 1 left. Recommendations for patient preparation, examination room arragements and other details of this examination are completely described in the project specifications that has been approved by the Ethical Committee of Antonio Pedro Universitary Hospital (HUAP) of Federal Fluminense University (Niterói, Rio de Janeiro, Brazil) and in the Brazilian Ministry of Health under number CAAE: 57078516.8.0000.5243.

The acquired images and patient data (from those that agree to be a voluntary in the research (signnig the consentiment term of the project) are available in http://visual.ic.uff.br/thyroid/ . The main goal of this research is to use the clinical patient data and knowledgement of where is their nodules to verify the possibilities of the use of machine learning thechniques to sugest possible malignant nodular areas in the patient ROI (Carvalho et al.. 2013). Following the ideas of others authors, the behavior of each point of ROI as temporal series is here studied. However during this examination even with a support for the head the patient moves on breafing or equilibrium modifications as can be seen on the superposition of the first and final frame showed in Fig. 1 center-left. Fig. 1 is created by the function “infusion” of the MatLab (where the black areas represents the room region; white areas are related to patient´s body commom for the both frames; magenta and green areas are used to represent areas of only one of the two frames (Mathworks, 2017). From this superposition of images is clear that in order to achieve each body point identification by coordinates of the frame is fundamental to find a way to describe the correspondence on points of ROI from the first image to all other in serie of images acquired on examination. That is a preprocessing must stablished how to follow the temperature change in each point of the skin surface. A new way to find these correspondence is by using tensorial analysis as considered in the next section (Conci, 1992).

3. TENSORS, VECTORS AND COORDINATE TRANSFORMATIONS

In linear algebra, a basis for a vector space of dimension *n* is a set of *n* vectors $\{e_1, \ldots, e_n\}$, called **basis vectors**, with the property that every vector in the space can be expressed as a unique linear combination of these basis vectors. The representation of operators and some elements are also determined by the chosen basis. Since it is necessary often to work with more than one basis for a vector space, it is of fundamental importance to be able to easily transform coordinate-wise representations of those taken with respect to one basis to their equivalent representations with respect to another basis. Such a transformation is called a **change of basis**.

Given a basis and a set of reference axes, a change of the reference axes corresponds to a change of elements that are referred by using such a basis. For instance, the quantitative description of certain physical entities are considered as scalars, vectors, covectors and tensors related to the way they transform under more general changes of basis. Each entity answers in the same manner, i.e. exhibit the same type of behaviour under axial changing. A scalar is invariant under transformations of basis. When the basis is changed, the *components* of a vector change by a linear transformation described by a matrix. Covectors change by the inverse matrix (Meriam, 1979).

In applications, vectors typically arise as the outcome of a measurement or group of measurements, and is represented as a list (or tuple) of numbers such as (x, y, z) or (x_1, x_2, x_3). The cardinality of this list depends on the choice of the axis or coordinate system. For instance, if the vector represents position with respect to an observer (a point in a specific coordinate system), then the new coordinates may be obtained from a reference axes, along which the components (x, y, z) or (x_1, x_2, x_3) are measured. For a vector, it must be possible to describe how it looks in any other coordinate system. That is to say, how the components of the vectors will be transformed from one coordinate system to another.

In general, indices can range over the indexing set (e.g. {x, y, z} or $\{x_1, x_2, x_3\}$ or {1,2,3}) including an infinite one. An index set being summed over is called the *summation index set*, in this case "*i*". It is also called a *dummy index* since any symbol can replace "*i*" without changing the meaning of the expression provided that it does not collide with index symbols in the same term. An index that is not summed over is a *free index* and should appear only once per term. If such an index does appear, it also usually appears in terms belonging to the same sum, with the exception of special values such as zero. This indexing **convention** led Einstein to improve the convention by including the rule: “repeated indices imply the summation” (Cyganski and Orr, 1988).

According to this convention, when an index variable appears twice in a single term and is not otherwise defined, it implies summation of that term over all the values of the indices, *i.e.* the index *i* do range over the set {1, 2, 3}:

$$y = \sum_{i=1}^{3} c_i x^i = c_1 x^1 + c_2 x^2 + c_3 x^3 \tag{1}$$

or simply $\boldsymbol{y} = \boldsymbol{c_i}\ \boldsymbol{x^i}$ the upper *i* is not exponent but means referential coordinate, coefficient of basis vectors. That is, in this context $\boldsymbol{x}^2$ should be understood as the second component of $\boldsymbol{x}$ rather than the square of $\boldsymbol{x}$. The upper index position in $\boldsymbol{x^i}$ is because, typically, an index occurs once in an upper (superscript) and once in a lower (subscript) position in a term. The virtue of Einstein improvement in notation is that it represents the variant quantities with simplicity. For instance, the inner product (or *dot product)* is the sum of corresponding components multiplied together $v \bullet u = v^i u_i$. The matrix product of two matrices A_{ij} and B_{jk} is:

$$\mathbf{C}_{ik} = (\mathbf{AB})_{ik} = \sum_{j=1}^{N} A_{ij} B_{jk} \quad \text{-}\blacktriangleright \quad C^i{}_k = A^i{}_j B^j{}_k \qquad (2)$$

According to **Einstein summation convention**, when an index variable appears twice in a single term and is not otherwise defined it implies summation of that term over all the values of the index. So indices can range over the set {1, 2, 3}. They can be represented as an array in line, *1xn*, being named row vectors, or alternatively as a column vectors: *nx1* array, i.e.

$$v = v^i e_i = \begin{bmatrix} e_1 & e_2 & \cdots & e_n \end{bmatrix} \begin{bmatrix} v^1 \\ v^2 \\ \vdots \\ v^n \end{bmatrix} \qquad w = w_i e^i = \begin{bmatrix} w_1 & w_2 & \cdots & w_n \end{bmatrix} \begin{bmatrix} e^1 \\ e^2 \\ \vdots \\ e^n \end{bmatrix} \qquad (3)$$

A contravariant vector has components that "transform" under changes of the coordinate reference axes (e. g., under rotation, translation, dilation, etc). The components of the vector change in a way that cancels the change in the spatial axes, so that the point (outcome or measurements) remains in the same position under coordinates change. In other words, if the reference axes were rotated in one direction, the component representation of the vector would rotate in exactly the opposite way. Similarly, if the reference axes were stretched in one direction (e.g. twice), the components of the vector, like the coordinates, would reduce (i.e. a half) in an exactly compensating way. Similarly, if the reference axes is translated in one direction (e.g. moves from 0,0,0 to -1,-1,-1), the components of the vector would be replace (addition of 1,1,1 in this case) in a compensating way. If the coordinate system undergoes a transformation described by an invertible matrix M, so that is axis x is transformed to $x'=Mx$. A vector v must be similarly transformed via $v'=M^{-1}v$.

This behavior is what distinguishes physical entities. For example a vector from a co-vector, or any other triple of physically meaningful quantities. For instance, if v consists of the v_1, v_2, and v_3-components of velocity, as v is a vector, if the coordinates of space are stretched, rotated, or twisted, then the components of the velocity transform in a compensating way. Examples of vectors include displacement, velocity and acceleration. On the other hand scalars, for instance, the size of a cube, is not a vector since a change in coordinate axis of the cube definition does not change the cube's length or volume because all these measures are scalars.

By contrast, a covector has components that change as the coordinates or, equivalently, transform like the reference axes. For instance, the components of the gradient vector of a function have this behavior: they transform like the reference axes. This is named contra variant and covariant transformations. The distinction between covariance and contra variance is particularly important for computations with tensors, which often have **mixed variance** (Conci, 1992). This means that they have both covariant and contra variant components, or both vector and covector behaviors. The valence of a tensor is the number of variant and covariant terms, and in **Einstein notation**, covariant components have lower indices, while contra variant components have upper indices, as presented in Eq. (3). A covariant vector varies more or less reciprocally to a corresponding contra variant vector. Expressions for lengths, areas and volumes of objects in the vector space can then be given in terms of tensors with covariant and contra variant indices. Under simple motions of objects (like uniform expansions, contractions, translations and rotation) the change of their points can be considered as the coordinates transformation on reciprocity in an exact manner. However, under more generic affine transformations of both representation is no longer possible.

4. MAIN COORDINATE AXIS

The ideas presented in last section are used in this work as a solution to the problem of tracking the temperature of a specific point along regions of interest (ROI) in an examination studying the thyroid area of a patient. By referring collectively to $\boldsymbol{e}_1,\boldsymbol{e}_2,\boldsymbol{e}_3$ as the $\boldsymbol{e}$ basis and to $\boldsymbol{n}_1$, $\boldsymbol{n}_2,\boldsymbol{n}_3$ as the $\boldsymbol{n}$ basis, the matrix containing all the $\boldsymbol{c}_{ik}$ is known as the transformation matrix from $\boldsymbol{e}$ to $\boldsymbol{n}$ or in case that "rotation" is the motion from one basis to another the "**direction cosine matrix** from $\boldsymbol{e}$ to $\boldsymbol{n}$" (because it contains only direction cosines). The properties of rotational matrix are such that its inverse is equal to its transpose. This means that the "rotation matrix from $\boldsymbol{e}$ to $\boldsymbol{n}$" is the transpose of those from $\boldsymbol{n}$ to $\boldsymbol{e}$.

Direction cosines or **directional cosines** are the contributions of each component of the basis to a unit vector in that direction. More generally, **directional cosine** refers to the cosine of the angle between any two vectors or co-vectors. They are useful for forming directional cosine matrices expressing one set of orthonormal basis in terms of another set, or for expressing a known coordinate (or any vector) in a different basis. Naming α, β and γ the direction cosines of a Cartesian coordinate axis, a, b and c the direction angles of the vector $\boldsymbol{v}$, considering the inner product definition, and the direction angles a, b and c , then the angles formed between $\boldsymbol{v}$ and the unit basis vectors ($\boldsymbol{e}_x$, $\boldsymbol{e}_y$, $\boldsymbol{e}_z$) are:

$$\alpha = \cos a = (v.\ \boldsymbol{e}_x)/\ |v|\ , \qquad \beta = \cos b = (v.\ \boldsymbol{e}_y)/\ |v|\ , \qquad \gamma = \cos c = (v.\ \boldsymbol{e}_z)/\ |v| \qquad (4)$$

It follows that $0 \leq \alpha \leq \pi$, $0 \leq \beta \leq \pi$, $0 \leq \gamma \leq \pi$ and $cos^2\, a + cos^2\, b + cos^2\, c = 1$. Returning now to unitary bases $\boldsymbol{e}_1$, $\boldsymbol{e}_2$, $\boldsymbol{e}_3$ and $\boldsymbol{n}_1$, $\boldsymbol{n}_2$, $\boldsymbol{n}_3$ all the possible **directional cosines** among elements of the 2 basis can be defined by $\boldsymbol{c}_{jk} = \boldsymbol{n}_j \cdot \boldsymbol{e}_k$ from the transformation matrix from *e* to *n*, or the rotation matrix from *e* to *n*.

Each acquired digital image in an examination (see Fig. 1), after being transformed to black and white, can be considered a 2-dimensional object where each point *(i,j)* can be represented as *B(i,j)=z* , and where *z={ 0, 1}*. Most of the times, 1 corresponds to the object (white pixels) and 0 to the background (black pixels) as in Fig. 1 (center-right). The generic moment of area of this object of order *p+ q*, is defined as Eq. (5) (Conci et al., 2008):

$$m_{pq} = \sum_{i=0}^{N} \sum_{j=0}^{N} B(i,j)(i)^p (j)^q \tag{5}$$

The centroid coordinates or center of geometry (CG) are defined by $\boldsymbol{m}_{01}/\boldsymbol{m}_{00}$ and $\boldsymbol{m}_{10}/\boldsymbol{m}_{00}$. Using these coordinates of the centroid it is possible to find the geometric moments of an object's area in relation to the coordinates passing through such a point, that is to compute the moments in relation to the axes parallel to the original one but with the origin (0,0) on the centroid. The choice for this axis is interesting because in this new coordinate system, the orientation of the image becomes invariant under translation of the object. Equation (6) describes the moments of order ***p+q*** around the centroid (Conci et al., 2008).

$$\mu_{pq} = \sum_{i=0}^{N} \sum_{j=0}^{N} B(i,j)(i - x_0)^p (j - y_0)^q \tag{6}$$

Although it is possible to have infinite set of orthogonal axes passing by the CG, there is a unique configuration where there are no second order central moments around both axes, *i.e.* $\boldsymbol{\mu}_{11}$=0. This axial configuration is called the **principal axis of an object**. Moreover, this unique orthogonal axis allows referring to an object point as invariant under rotation of the object. So, invariance of the object to under rotation is obtained by identifying the main axes passing through the centroid of the object (seeing in Fig. 1 right). The orientation of the main coordinates is defined by the angle $\boldsymbol{\theta}$ from Eq. (7).

$$tan(2\theta) = \frac{2\mu_{11}}{(\mu_{20} - \mu_{02})} \tag{7}$$

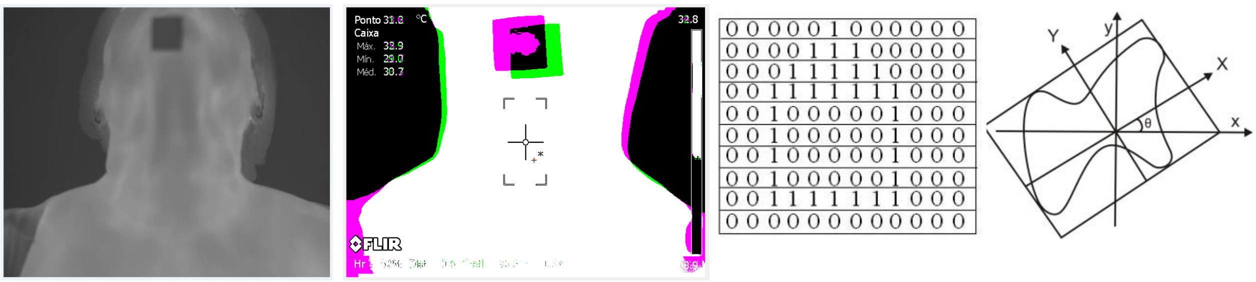

Figure 1. One frame of the examination, two frames superimposed, 2D binary object: ***B(i,j)=1***, and two orthogonal axis passing by a CG of other object showing the angle of Eq. (7)

5. AN APPROACH FOR FOLLOWING ROI´S POINTS

Fig. 2 presents two frames of an IR examination in gray scale, their ROIs in Black and White (Sezgin & Sankur, 2004); these ROIs are superimposed by matching their centroids and main axes. The bigger image in Figure 2 shows that possible mismatching can appear far from the origin of the main axis, where the possibility of nodules or important elements is very low, so it appears that the ideas of following the patients point using their description of each frame related to the main axis of the patient can be investigated as a possible methodology for construction of temporal series. We implemented this and used it in 190 frames, matching images of 10 patients. We name this approach the Principal Axis – PA approach.

In order to make a comparative study for evaluating this idea, we use a single computer in which we compare both approaches for defining correspondence among points in same images. This second approach uses a combination of 2 softwares to find the best points of correspondence between the images of a patient. First, points on the frames are selected as the best local descriptors using the Scale-Invariant Features Transform (SIFT) software (Lowe, 2004), followed by the RANdon Sample Consensus (RANSAC) tool that is used to reduce significantly different samples (Outliers) (Fischer & Bolles,1981). After that, considering the best couple of points in each two of the frames to be aligned by the closest pair of points, all possible isometric transformations between the 2 frames are computed (Zargochev & Goshtasby, 2006), and the correlation of the resulting images computed by using MatLab (Mathworks, 2017). The transformation that presents best correlation coefficient is considered for using to make the correspondence among the points of the ROI region of the 2 frames by affine transformation. We name this approach the SIFT+ RANSAC –S+R approach.

Table 1 presents the results of the 2 approaches in terms of the quality of the results and the execution time. Quality is measured by the correlation coefficient and can range from -1.0 to 1.0, with a value of 1.0 indicating a perfect correlation (Conci et al, 2008). So, in this table, bigger values in columns 2 and 3 present best results. To better see the approach that presents higher quality for each examination, see Table 1, the column with several values in bold. The PA approach shows more adequate results in 9 of the 10 examinations considering quality. Moreover, considering time the S+R approach needs, on average, more than 5 times the PA approach, allowing us to say that then using PA the transformation of points along the examination can be done in the proper time with very little standard deviation in computational time.

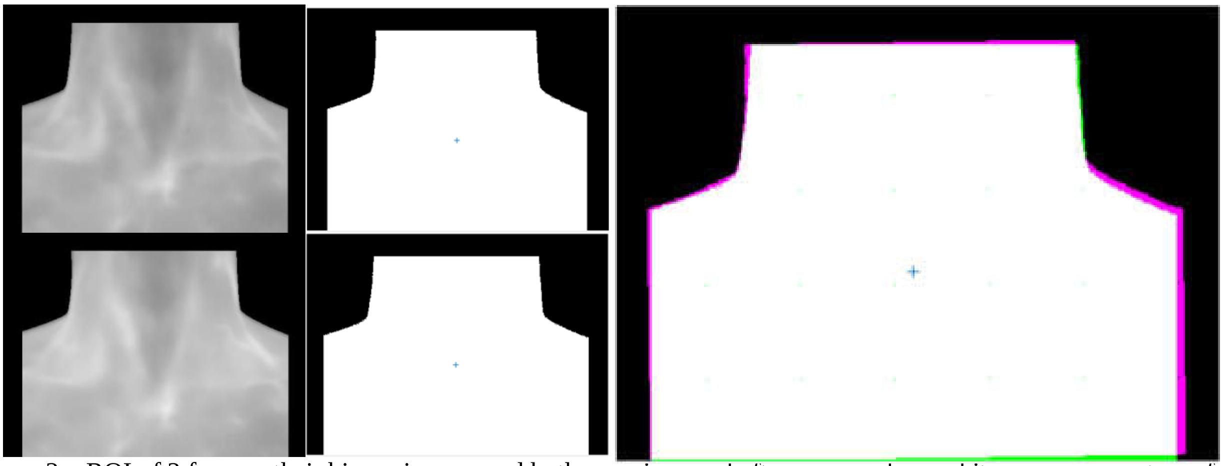

Figure 2 – ROI of 2 frames, their binary images and both superimposed after zoom, where white area represents perfect match inside the ROI, green or magenta are areas belonging to only one of the 2 frames**.**

Table 1. Results the 19 matching of the 2 approaches for 10 examinations.

Patient	Average of correlation		Total processing time per examination (seconds)	
	PA	S+R	PA	S+R
12/09/2016-01	**0.9940**	0.9882	9.92	53.56
19/09/2016-02	**0.9979**	0.9973	9.97	52.39
19/09/2016-03	**0.9955**	0.9909	9.94	52.95
19/09/2016-04	0.9836	**0.9882**	9.77	52.53
03/10/2016-01	**0.9899**	0.9868	9.96	52.61
03/10/2016-02	**0.9894**	0.9877	9.83	53.37
03/10/2016-03	**0.9893**	0.9891	9.89	53.17
10/10/2016-01	**0.9944**	0.9873	10.04	53.13
10/10/2016-02	**0.9935**	0.9889	9.53	52.18
10/10/2016-03	**0.9920**	0.9873	10.05	51.62
Mean of 190 matching	**0.9920**	0.9892	9.89	52.751
Standard deviation of 190 matching	0.0041	0.0031	0.1529	0.5963

6. CONCLUSIONS

In dynamic infrared thermography, using computer aided examination; sequences of temperature of each anatomic point are used to analyze the body behavior over time. However, to do this the points of the captured images must been considered. An important aspect of any technique to been used for this purpose is that such an approach must maintain original intensity values of the image. This is not a characteristic of most registration techniques frequently used for other types of image registration methodology.

In this paper, the idea of use the main axis of the Region of Interest was proposed to define the coordinates of such a point in an examination. This technique was implemented and compared with other techniques using combinations of techniques available for image registration. Table 1 compares the results of both techniques, and was founded that new technique proposed here produces better results in 9 of the 10 cases. Moreover, while for the Principal Axis Approach the processing time necessary to process all 20 images of one examination is around 10 seconds, other technique always need more then 50 seconds to do the same task. In future works we will intend to test such techniques considering a larger number of images and use the temporal series of temperatures in the machine learning method in order to implement a system to aid thyroid nodule classification.

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8. RESPONSIBILITY FOR INFORMATION (RESPONSABILIDADE PELAS INFORMAÇÕES)

The authors are the uniquely responsible for the information included in this work. (Os autores são os únicos responsáveis pelas informações incluídas neste trabalho).