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Uncertainty as key element in the analysis of X-ray angiography images

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Abstract. The X-ray angiography images are routinely used to assess the blood vessels. The acquisition procedure considers a medical imaging system which allows obtaining views of the vessel while the blood flows thought them. The X-ray source is influenced on the region to be viewed and then, the projection of the all anatomical structures in the champ of view is shown through an image intensifier. The information of the blood vessel is impacted for the other structures. Additionally, the blood and the contrast product required in the acquisition are not mixed homogeneously, producing artifacts in the images. Finally, the noise is also an impact factor in the quality of the angiography images. In the coronary vessel case, the branches of the network are superposed. In this paper, an enhancement procedure to diminish the uncertainty associated to X-ray angiography images is reported. The relation between two versions of the angiograms is determined using a fuzzy connector considering that this relation diminishes the images intrinsic uncertainty. These versions correspond with images filtered with low-pass and high-pass image filters, respectively. The technique is tested with images of the coronary and kidney vessels. The qualitative results show a good enhanced of the angiography images.

1. Introduction

In the clinical routine, the blood vessel dynamic exploration is performed using of X-ray angiography images which provide relevant information on human hemodynamics, allowing this imaging method the intraoperative orientation course [1]. X-ray angiography or fluoroscopy remains today as the most commonly used intraoperative imaging technique because features such as fast handling, easy to use, able to be trusted, and ability to pinpoint the location of the surgical instrument [2]. This radiological procedure has been used to observe blood flow in any organ in the body, such as coronary arteries in cardiac angiography [3], the brain irrigation in vascular angiography [4], the left ventricle cavity in ventriculography [5], and renal artery damage in renal angiography [6], stand out.

Considering that angiography is a gold standard for intraoperative navigation in blood dynamics, several authors have developed computational models to assist the diagnosis [7–9]. However, such models consider certain assumptions to solve the problems associated with the radiological image acquisition processes. In the process of model construction must be considered that the blood and the contrast agent is not homogeneously mixed, the overlapping anatomical

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structures in the acquisition field of view, involuntary movement of the patient, noise and the artifacts [10]. The indicated image acquisition process issues impact the X-ray angiography data quality, therefore the modelling and diagnosis [11].

The impact of these issues on radiological images, generates uncertainty about the data that the clinical specialists analyzing [12]. The uncertainty can be theoretically explained using epistemic uncertainty [13]. The aim of the theory is to match information not known as known through reliability models. An alternative to finding the explanation of epistemic uncertainty based on the extension of the notion of set is within fuzzy set theory [14]. Several authors have dedicated their researches to demonstrate the usefulness of the fuzzy set theory in image processing, a particular research interest is related to the development of techniques related to filtering and image enhancement [15–18].

This paper exploits the fuzzy sets theory to relate relevant information extracted from X–ray angiograms in order to diminish the intrinsic uncertainty of these medical images. The idea is to combine the information of the angiography images by means fuzzy connectors. These fuzzy connectors are operators considered for constructing the intersection of the fuzzy sets [19]. Fuzzy connectors have been used to associate uncertain data sets, but with the best attributes in order to obtain an output set with the best features of the related data. Certain fuzzy connectors have been used to generate crossover operators in order to increase the performance of real-coded genetic algorithms [20].

In this work, the fuzzy connectivities are used to establish a relationship between two versions of an X–ray angiography image. This relationship is considered as an enhancement procedure, useful to diminish the intrinsic uncertainty of the images and consequently increase the original angiogram quality. Coronary and renal vessels images are considered. Low-pass and high-pass image filters are used for obtaining the versions of the image to be related.

2. Materials and methods

2.1. Materials

X-ray angiography images of the coronary arteries and renal arteries are considered in this study. Coronary network supply oxygenated blood to the myocardial muscle meanwhile the renal arteries are the blood vessels through which blood flows to the kidneys. The angiographic exploration requires the insertion of a catheter through the main artery, normally, it is inserted into the aorta at the groin level. The catheter is guided to the arteries and then, a contrast product is released. After, a set of X-ray projections is acquired in order to view how blood flows through the vessels.

An Innova TM 4150 General Electric Medical System corresponds to the digital flat-panel X-ray system used for acquiring the mono-plane sequences of the coronary and renal vessels. The coronary vessels images are acquired using the right anterior oblique view of 30° , meanwhile the renal arteries images required of caudal or cranial angulation of 15° to 20° . All images have a spatial resolution of 512×512 pixels. The considered pixel size is 0.285×0.285 mm and the pixels are quantified to 12 bits. Figure 1(a) shows a coronary angiography and Figure 1(b) a renal angiography.

2.2. Methods

2.2.1. Fuzzy connectors. Fuzzy connectors for data with low, moderate and high degrees of uncertainty are considered. The fuzzy operations of intersections and unions are based on triangular norms (T-norm), triangular co-norms (T-conorm), averaging functions and generalized compensation operators [21, 22]. In this work, the logic fuzzy connectors are considered and their T-norm, T-conorm, averaging functions and generalized compensation

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operators correspond with to the Equation (1), Equation (2), Equation (3) and Equation (4), respectively.

$$T(x,y) = \min\{x,y\},\tag{1}$$

$$G(x,y) = max\{x,y\},\tag{2}$$

$$P(x,y) = (1 - \psi x) + \psi y, \forall \psi \in [0,1],$$
(3)

$$C(x,y) = T^{1-\psi} \cdot G^{\psi}.$$
(4)

In order to establish the fuzzy connectivities, four functions F, S, M, and L of $[a, b] \times [a, b]$ in $[a, b] \forall a, b$ in the reals are defined considering the constraint shown in the Table 1.



Figure 1. (a) Coronary angiography. (b) Renal angiography.

Table 1. Constrains of F, S, M and L functions.	
Conditions	Constrains
$\forall c, cp \text{ in } [a, b]$	$\begin{array}{l} F(c,cp) \leq \min\{c,cp\} \\ S(c,cp) \geq \max\{c,cp\} \\ \min\{c,cp\} \leq M(c,cp) \leq \max\{c,cp\} \\ F(c,cp) \leq M(c,cp) \leq S(c,cp) \\ F, S, M \text{ and } L \text{ are monotonous increasing functions} \end{array}$

The logic fuzzy connectors are associated with the F, S, M and L functions by means the linear transformations shown in Equation (5), Equation (6), Equation (7) and Equation (8).

$$F(c,cp) = a(b-a)T(s,sp),$$
(5)

$$S(c, cp) = a(b-a)G(s, sp),$$
(6)

$$M(c,cp) = a(b-a)P(s,sp),$$
(7)

$$L(c,cp) = a(b-a)C(s,sp),$$
(8)

where $s = \frac{(c-a)}{(b-a)}$ and $sp = \frac{(cp-a)}{(b-a)}$ and represent the normalized values of the images to relate.

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2.2.2. Image filters. Coronary and renal angiograms are initially processed with low-pass and high-pass filters [23]. The anisotropic diffusion filter is considered as the low-pass filter [24] and the Gaussian high-pass filter [25]. Anisotropic diffusion filters can be expressed mathematically according to the Equation (9).

$$\frac{dI(x,y,t)}{dt} = \nabla c(x,y)\nabla I(x,y,t),\tag{9}$$

where I(x, y, 0) represents the original image, t is equal to time, and c is the conductance or diffusion force as a function of (x, y). Anisotropic diffusion is used to attenuate noise, preserving or enhancing edges, it is used in edge detection algorithms in order to perform the image smoothly within the regions delimited by the edges and not through them [26].

The Gaussian high pass filters are designed to attenuate the low frequencies of the image to be processed, in the Fourier space, by means of a filter whose transfer function is represented by a Gaussian curve [27]. The Figure 2 shows the Gaussian high–pass filter transfer function.



Figure 2. Transfer function of the Gaussian high pass filter.

Figure 3 shows the results obtained from applying the anisotropic diffusion filter and the Gaussian high–pass filter to the images shown in Figure 1. The images in the first row correspond to the coronary and renal angiograms low–pass filtered, while in the second row the results obtained when filtering high–pass such images are shown.

2.2.3. Enhancement procedure The radiological projections of each angiographic sequence, namely coronary and renal, are filtered by the anisotropic diffusion filter and with the Gaussian high pass filter. These versions of the original projections contain relevant information at the high and low frequencies in the Fourier space. This low and high frequency information is supposed to contain the best attributes of the images, which can, when combined, reduce the uncertainty associated with the issues generated in the process of acquisition of the radiological sequences.

Considering that c corresponds to each of the intensities of the low-pass filtered image and cp with the intensities of the high-pass filtered image, and also that a and b represent the maximum and minimum values that the intensities can take. The two versions of the angiograms, namely, low-pass filtered and high-pass filtered, can then be combined as fuzzy sets using the fuzzy connectivities expressed as linear transformations in the Equation (5), Equation (6), Equation (7) and Equation (8). The result of each of these combinations is supposed to generate a new image in which the degree of uncertainty is lower, and consequently an image with a higher quality.



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Figure 3. Low-pass and high-pass filtered images.

3. Results

The enhancement procedure is applied to coronary angiography images and the renal angiography images. The idea is to process the low-pass and high-pass image versions for each of the fuzzy connectives. The four images, thus obtained for each angiogram type, are then visually inspected in order to assess the improvement obtained by each fuzzy combination.

Figures 4 and Figure 5 show the results achieved by combining the two versions of the radiological images with the logic fuzzy connectors. In each figure, the first row represents the result of applying the fuzzy connectivities derived from the T–norm and the resulting image of the fuzzy operator based on the T–conorm; meanwhereas, the second row shows the image enhanced with the averaging functions, and the enhancement result achieved with the generalized compensation operators.

The analysis of the results obtained from angiograms data by visual inspection is based on the hypothesis that an image with sharp or enhanced edges is usually more pleasing subjectively than the original image. The images of the Figures 4 and Figure 5 show the utility of the fuzzy connectivities based on T-norm, T-conorm and the averaging functions to detect the edges of the cardiac anatomical structures viewed in the coronary and renal angiography images. In fact, these fuzzy connectors can be thought of as edge detector operators. The generalized compensation operators have been observed to yield better results than the others fuzzy connectors in terms of image enhancement technique performance.

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Figure 4. Coronary angiography images enhanced.



Figure 5. Renal angiography images enhanced.

4. Conclusions

An X-ray angiography enhancement technique of the coronary and renal vessels is presented, focused on reducing information uncertainty using fuzzy connectors. Qualitative results show an improvement of angiography images using generalized compensation logic operator.

As future work it is proposed to perform a quantitative analysis of the improvement in order to determine the uncertainty reduction index.

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