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Segmentation of dental X-ray images in medical imaging using neutrosophic orthogonal matrices

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ABSTRACT

Over the last few decades, the advance of new technologies in computer equipment, cameras and medical devices became a starting point for the shape of medical imaging systems. Since then, many new medical devices, e.g. the X-Ray machines, computed tomography scans, magnetic resonance imaging, etc., accompanied with operational algorithms inside has contributed greatly to successful diagnose of clinical cases. Enhancing the accuracy of segmentation, which plays an important role in the recognition of disease patterns, has been the focus of various researches in recent years. Segmentation using advanced fuzzy clustering to handle the problems of common boundaries between clusters would tackle many challenges in medical imaging. In this paper, we propose a new fuzzy clustering algorithm based on the neutrosophic orthogonal matrices for segmentation of dental X-Ray images. This algorithm transforms image data into a neutrosophic set and computes the inner products of the cutting matrix of input. Pixels are then segmented by the orthogonal principle to form clusters. The experimental validation on real dental datasets of Hanoi Medical University Hospital, Vietnam showed the superiority of the proposed method against the relevant ones in terms of clustering quality.

1. Introduction

Electronic technology grew remarkably over the last few decades with more powerful computer equipment, cameras and medical devices (Goyal, Beg, & Ahmad, 2017; Kieu, Vo, Le, Deng, & Le, 2017; López, López, de la Torre Díez, Jimeno, & López-Coronado, 2016; Mai, Vo & Nguyen, 2017; Vo, Pham, Le, & Deng, 2017). New medical devices such as the X-ray machines, tomography, magnetic resonance imaging, radiation scans, etc. are present to support professional works of clinicians (Ngan, Tuan, Son, Minh, & Dey, 2016). The on-going development of imaging technology helped to solve many challenges in medical imaging today (Rad, Rahim, & Norouzi, 2014). Medical imaging has made an important contribution to improving the accuracy, timeliness and efficiency of diagnosis (Nowaková, Prílepok, & Snášel, 2017). As based on ultrasound images, physician can accurately measure sizes of typical organ in abdominal cavity (namely liver, spleen, kidneys, pancreas, etc.) and detect abnormal tumors (Setarehdan & Singh, 2012). It helps the physician identify cranial pathologies, especially endoscopic hemorrhoids and brain tumors, and accurately determine abnormalities and masses in the body (Wang et al., 2016).

One of the most crucial tasks in medical imaging is **segmentation,** which divides a medical image into segments for further studies on diseases (Narkhede, 2013). Many algorithms have been developed for the purpose of medical segmentation. The *first approach* is the pixel-based and histogram division method (Nomir & Abdel-Mottaleb, 2005; Rad, Mohd Rahim, Rehman, Altameem, & Saba, 2013; Xu, Xu, Jin, & Song, 2011). The advantages of this method are simple and low in cost, but its disadvantage is sensitivity with threshold values (Rad et al., 2013). The *second approach* is leveling for forward propagation, which is applicable to medical imaging purposes (Bhandari, Kumar, Chaudhary, & Singh, 2016; Dougherty, 2009; Somu, Raman, Kirthivasan, & Sriram, 2016; Zhou & Abdel-Mottaleb, 2005). The advantage of this method is that no complex data structure is used, but it only works when decomposing (Bhandari et al., 2016).

The *last group* - fuzzy clustering divides the data into clusters and determines pixels belonging to those groups (Ayech & Ziou,

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2015; Bezdek, Ehrlich, & Full, 1984; Son, 2014a,b,c, 2015a,b,c, 2016a,b, Son, Tuan, Fujita, Dey, Ashour, Ngoc& Chu, 2018; Son, Cuong, Lanzi, & Thong, 2012; Son, Cuong, & Long, 2013; Thong & Son, 2015, 2016a,b,c; Tuan, Ngan, & Son, 2016). This algorithm is simple, easy to set up, requiring fair computation complexity; yet the downside is sensitivity to interferences and extraneous elements in the data (Ayech & Ziou, 2015). For instance, some semi-supervised fuzzy clustering frameworks that integrate the spatial constraints and interactive fuzzy satisficing for dental x-ray image segmentation have been presented in Son and Tuan (2016, 2017) and Tuan et al. (2016). So far, there have been some advanced extensions of the fuzzy clustering such as the picture fuzzy clustering, fuzzy geographically weighted clustering, etc., that are likely to apply to the dental x-ray image segmentation (Son, 2014a,b,c, 2015a,b,c, 2016a,b, Son et al., 2012, 2013, 2018; Thong & Son, 2015, 2016a,b,c; Son & Louati, 2016, Son & Thong, 2015, Son & Van Hai, 2016; Son, Wijayanto, & Purwarianti, 2016; Son, Linh, & Long, 2014). Among three groups, the fuzzy clustering group is the most typical one for segmentation of medical images because of its flexibility and adaptability to any kind of images (Nayak, Naik, & Behera, 2015). Nonetheless, it should be further extended on an advanced fuzzy set to gain better representation of medical images (Zhang, Zhang, & Cheng, 2010).

Neutrosophic set (NS) (Smarandache, 2015) is indeed the advanced fuzzy set that is appropriate for such an application. It is defined as a set where each element of the universe has degrees of truth (T), indeterminacy (I) and falsity (F) that lie in the non-standard unit interval, respectively. The uncertainty is the indeterminacy factor which is independent of truth and falsity values while the incorporated uncertainty is dependent on the degrees of belongingness and non-belongingness (Smarandache, 2015). This can handle the problems of sensitivity to interferences and extraneous elements in the data that are remained in the fuzzy clustering (Smarandache, 2015). There are some works that applied neutrosophic approach to image segmentation. Cheng and Guo (2008) regarded an image in the neutrosophic domain including three subsets T, I and F for image thresholding. Guo and Cheng (2009) performed image segmentation using a γ-means clustering. Guo, Cheng, and Zhang (2009) investigated image denoising by the neutrosophic approach. Zhang et al. (2010) employed a watershed algorithm to perform image segmentation in the neutrosophic set. Cheng, Guo, and Zhang (2011) improved Fuzzy C-Means (FCM) on the neutrosophic set for image segmentation with a new α-mean operation for reducing set indeterminacy. There are many works that applied the neutrosophic set for image segmentation; yet they have not been designed for the medical segmentation so far.

In this paper, we aim to **propose a new fuzzy clustering** algorithm for dental x-ray image segmentation based on the neutrosophic set especially the new notion – neutrosophic orthogonal matrix. It converts each pixel of the input image into the neutrosophic sets which are then used to compute the neutrosophic similarity matrix. The cutting matrix is then generated from the neutrosophic similarity matrix which further shapes the clusters of pixels. The new algorithm is validated against the relevant methods with respect to the cluster quality and computation time. Experimental results on real Dental X-Ray datasets (Ngan et al., 2016) confirm the efficiency of the proposal. The new algorithm overcomes disadvantages of the previous algorithms; thereby improving the quality of analysis and diagnosis.

This paper is structured in 5 main sections: Section 1 introduces the content of the article, Section 2 presents preliminary concepts of the neutrosophic set and neutrosophic approaches to image segmentation. Section 3 proposes the clustering method, Section 4 validates it experimentally and lastly Section 5 concludes the paper.

2. Preliminary

2.1. Neutrosophic set

Definition 1. (Smarandache, 2015)**: Neutrosophic Set (NS).**

Let X be a non-empty set and$x \in X$. A neutrosophic set A in X is characterized by a truth membership functionT_A, an indeterminacy membership functionI_A, and a falsehood membership functionF_A. Here, $T_A(x)$, $I_A(x)$ and $F_A(x)$ are real standard or non-standard subsets of $]0^-,\ 1^+[$ such that T_A,I_A,F_A: $X \to]0^-,\ 1^+[$. There is no restriction on the sum of $T_A(x)$,$I_A(x)$ and$F_A(x)$, so that $0^- \le T_A(x)+I_A(x)+F_A(x) \le 3^+$. From philosophical point view, the neutrosophic set takes the value from real standard or non-standard subsets of $]0^-,\ 1^+[$. Thus, it is necessary to take the interval [0, 1] instead of $]0^-,\ 1^+[$for technical applications because it is difficult to use $]0^-,\ 1^+[$ in real life applications such as engineering and scientific problems.

If the functions $T_A(x)$, $I_A(x)$ and $F_A(x)$ are singleton subinterval/subsets of the real standard such that $T_A(x)$: $X \to [0,\ 1]$, $I_A(x)$: $X \to [0,\ 1]$, $F_A(x)$: $X \to [0,\ 1]$ then a simplification of the neutrosophic set $A$is denoted by,

$$A = \{(x, T_A(x),\ I_A(x),\ F_A(x)) : \ x \in X\}. \tag{1}$$

with $0 \le T_A(x)+I_A(x)+F_A(x) \le 3$. It is a subclass of neutrosophic set and called simplified neutrosophic set.

Definition 2. (Smarandache, 2015)**:** Let $A_1 = \{\langle x;\ T_1(x);\ I_1(x);\ F_1(x)\rangle | x \in X\}$ and $A_2 = \{\langle x;\ T_2(x);\ I_2(x);\ F_2(x)\rangle | x \in X\}$ be two neutrosophic sets. Some operations on the neutrosophic set are given below:

1 $A_1 \subseteq A_2$ if and only if $T_1(x) \le T_2(x)$; $I_1(x) \ge I_2(x)$; $F_1(x) \ge F_2(x)$,
2 $A_1^c = \{\langle x; F_1(x); I_1(x); T_1(x)\rangle | x \in X\}$,
3 $A_1 \cap A_2 = \{\langle x;\ \min\{T_1(x);\ T_2(x)\};\ max\{I_1(x);\ I_2(x)\};\ max\{F_1(x);\ F_2(x)\}\rangle | x \in X\}$,
4 $A_1 \cup A_2 = \{\langle x;\ \max\{T_1(x);\ T_2(x)\};\ min\{I_1(x);\ I_2(x)\};\ min\{F_1(x);\ F_2(x)\}\rangle | x \in X\}$.

Definition 3. (Smarandache, 2015)**:** Let $V_j (j = 1, 2)$ be two ordinary subsets, and $M \subseteq V_1 \times V_2$ an ordinary relation. Then for any $e, f \in V_2$, $Mf = \{e | eMf\}$ and $eM = \{e | eMf\}$ are respectively called a former set and a latter set.

2.2. Neutrosophic approach to image segmentation

Definition 4. (Cheng & Guo, 2008)**: Neutrosophic Image.**

Let U be a universe of discourse and W be a set included in U, which is composed of bright pixels. A neutrosophic image PNs is characterized by three subsets T, I and F. A pixel P in an image is described as $P(T,\ I,\ F)$ and belongs to W in the following way: it is $t\%$ true in the bright pixel set, $i\%$ indeterminate, and $f\%$ false, where t varies in T, i varies in I, and f varies in F. Each component has a value in [0, 1]. Pixel $P(i,\ j)$ in the image domain is transformed into neutrosophic domain: $PNS(i,\ j) = \{T(i,\ j),\ I(i,\ j),\ F(i,\ j)\}$. $T(i,\ j)$, $I(i,\ j)$ and $F(i,\ j)$ represent probabilities belonging to white set, indeterminate set and non-white set, respectively defined as,

$$T(i, j) = \frac{g_{ij} - g_{min}}{g_{max} - g_{min}}, \tag{2}$$

$$I(i, j) = 1 - \frac{H0_{ij} - H0_{min}}{H0_{max} - H0_{min}}, \tag{3}$$

$$F(i, j) = 1 - T(i, j), \tag{4}$$

$$H0(i, j) = |e(i, j)|, \tag{5}$$