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POLYPS RECOGNITION USING FUZZY TREES

CHUQUIMIA Orlando¹, PINNA Andrea¹, DRAY Xavier², BERTRAND Granado¹

Abstract—In this article, we present our work on classifier to realize a Wireless Capsule Endoscopy (WCE) including a Smart Vision Chip (SVC). Our classifier is based on fuzzy tree. We obtain a sensitivity of 88.56% and a specificity of 86.42% on a large database, that we have constructed, composed of 18910 images containing 3895 polyps from 20 different video-colonoscopies.

I. INTRODUCTION

Colorectal cancer is the second death cause by cancer around the world. It is a real public health problem with 694000 deaths in 2012 [3], 95% of colorectal cancer is originated from adenoma polyp degeneration [3].

To realize the detection of polyps, WCE was developed since 2000 [5]. This autonomous medical device is a simple pill that the patient swallows and that transmits images of the gastrointestinal tract via a Radio Frequency communication through the body. But this WCE presents some limitations as a low image resolution compared to standard colonoscopy, a large amount of unnecessary transmitted images, more than 50000 transmitted images and a limited energy budget.

To reduce the time to analyse the images produced, several automatic recognition algorithms to detect polyps were introduced [4] (we can see their performances in table I). We can notice that the most performant results were obtained with small amounts of images in the database. Although these

TABLE I

STATE OF THE ART RECOGNITION ALGORITHMS.

Authors	Images	Features 2D	Recall	Specificity
Kodogiannis[4]	140	Shape	97	94
Karagyris[4]	100	Colour, shape	96.2	70.2
Li & Meng[4]	1200	Colour, texture	91.6	NA
Bernal[1]	300	Shape	89.0	98.0
Romain[9]	1500	Shape, Texture	91.0	95.2
David[2]	30540	Colour, shape	80.0	65.0
Figueiredo[7]	18900	Colour, shape	81.0	90.0

algorithms help the physician and can limit the errors in human interpretation, they are not sufficient to increase the autonomy of the WCE nor the resolution of the images. To do so, we propose a new paradigm of WCE. Its originality is to integrate a SVC inside the WCE to give it the capability of recognizing a polyp in situ. With this quality, a WCE can transmit only suspicious images in order to reduce their number, increasing its autonomy and providing opportunities

to increase the image resolution. In this article, we present our work on the classifier to realize this WCE. It is based on fuzzy trees and allows the recognition of a polyp. We choose it for its high degree of integration in a system on chip [6].

II. POLYPS RECOGNITION

A. Feature extraction

In this method the classification is done on Region Of Interest (ROI) that correspond to a zone where there is a high suspicion of a presence of a polyp. We have delimited the ROI by hand based on the knowledge of a physician. We have extracted 2D texture and luminosity features of each ROI using the Co-occurrence Matrix. We extract 26 descriptors that become our attributes and we use them to train our fuzzy trees.

B. Fuzzy tree

Fuzzy tree classifier allows us to manage imprecise data improving the detection robustness and takes in to account lack of knowledge of the attributes or descriptors [8]. This inductive recognition algorithm consists of two parts: learning phase and classification phase.

C. Creation of dataset

We used a set of 20 video-colonoscopies, 10 of them contain polyps[10]. The dataset $\varepsilon\{A_1, A_2, \dots, A_{26}, C_{0,1}\}$ is a table of 27 columns where each row correspond to a ROI ε_i with 26 attributes ranging from A_1 to A_{26} and a class which it belongs "0" or "1". To construct the dataset and attach a class to each ROI, we use a ground-truth validated by a gastroenterologist. For the class "1", the ROI is extracted from the mask that was annotated by the gastroenterologist on an image. For the class "0" a randomly ROI selection is made. The dataset construction is illustrated in figure 1.

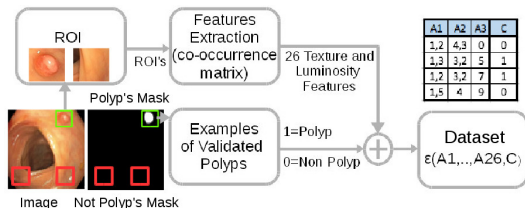


Fig. 1. Proposed diagram for the dataset creation.

We have obtained a dataset composed by 131038 ROI (3856 ROI of class "1"). After we have built 50 learning datasets composed by 4628 dataset's ROI where 50% belong to class "1". For the class "0" a random selection is made

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from the dataset. A test dataset of 6082 dataset's ROI was built and it is composed by 1542 ROI of class "1".

D. Learning phase

To construct a fuzzy tree $\Phi(\varepsilon_{\{A_i, C_k\}}, H, P, T)$ we use for each training dataset $\varepsilon_{\{A_i, C_k\}}$ a discrimination method H to discriminate which attributes are more important. We use a partition strategy P that gives the notion of how to divide the dataset of examples into two groups, and a stop criterion T that indicates when the training dataset is in its minimum expression indicating that the construction is completed. To construct a fuzzy tree from a training dataset we use the following criterions: a star entropy and Shannon entropy H modeled with entropy model proposed in [8], a fuzzy attributes aggregation called Generalized Fuzzy Partition using Mathematical Morphology (FPMM*), a classic partition P alpha-couple ($\alpha = 1/2$) and a stop criterion T when there are 5 or less examples in a sub-set.

At the end of the learning phase, we obtain a fuzzy tree composed by J membership functions $\mu_{j(x)}$ for each attribute and M rules: nodes corresponding to J attributes $A_{m(j)}$ for each rule, arcs corresponding to J break points $v_{m(j)}$ for each attribut and leaves corresponding to membership degrees μ_{mC_0} and μ_{mC_1} of each class of the rule.

E. Classification phase

To use fuzzy trees Φ to classify a observed objet $\varepsilon_i\{w_1, w_2, \dots, w_{26}\}$ we use the method of generalized Modus Ponem to classify precise datas described below.

- 1) We calculate a similarity degree Deg for the observed value $w_{m(j)}$ of each attribute j of the rule m , in this case $Deg(w_{m(j)}) = \mu_{j(w_{m(j)})}$.
- 2) We calculate a satisfiability degree $Fded_{m(c_k)}$ using all the similarity degrees $Deg(w_{m(j)})$ of the J attributes of the rule m .

$$Fded_{m(k)} = \top_{j=1, \dots, J} Deg(w_{m(j)}) * \mu_{mC_k} \quad (1)$$

In this case μ_{mC_k} corresponds to the Zadeh conditional probability $P^*(c_k / (v_{m(1)}, v_{m(2)} \dots v_{m(j)}))$

- 3) Finally, we calculate a new membership degree μ_{c_k} using all the satisfiability degrees of the M rules.

$$\mu_{c_k} = \perp_{m=1, 2, \dots, M} Fded_{m(k)} \quad (2)$$

We use the triangular norm \top and conorm \perp proposed by Zadeh et Lukasiewicz.

To mesure the classification rate we calculate a sensitivity and specificity. Sensitivity measures the ability to detect polyps and specificity measures the ability to detect the absence of polyp. We test our 50 fuzzy trees constructed on the test dataset for each classification method: Classical Modus Ponem, Zadeh and Lukasiewicz operators. In the figure 2 we show the average and standard deviation of all the sensitivity and specificity results for each classification method. We can notice, based on the analysis of figure 2, that Modus Ponem demonstrated higher sensitivity performance and a stable behavior.

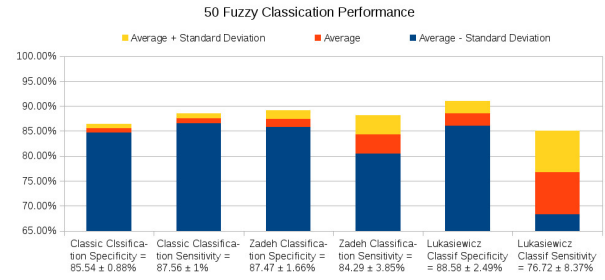


Fig. 2. Fuzzy Trees classification performance.

III. CONCLUSIONS

In this paper we have presented the fuzzy trees performance for the classification of polyps inside a WCE using texture and luminosity features. The experimentation has shown a sensitivity of 88.56% and a specificity of 86.42% using fuzzy trees. This is at the state of the art compared to other methods presented in table I, and validated in a large database of 18910 images.

Actually, we are integrating our method on a Xilinx Zynq-7000 board for measurement and validation of non-functional performance as the worst case execution time, energy consumption and the number of Slice Registers SR and LookUp Tables LUT needed.

REFERENCES

- [1] BERNAL, J., SÁNCHEZ, J., AND VILARINO, F. Towards automatic polyp detection with a polyp appearance model. *Pattern Recognition* 45, 9 (2012), 3166–3182.
- [2] DAVID, E., BOIA, R., MALAESCU, A., AND CARNU, M. Automatic colon polyp detection in endoscopic capsule images. In *International Symposium on Signals, Circuits and Systems ISSCS2013* (2013).
- [3] FERLAY, J., SOERJOMATARAM, I., DIKSHIT, R., ESER, S., MATHERS, C., REBELO, M., PARKIN, D. M., FORMAN, D., AND BRAY, F. Cancer incidence and mortality worldwide: sources, methods and major patterns in globocan 2012. *International journal of cancer* 136, 5 (2015), E359–E386.
- [4] IAKOVIDIS, D. K., AND KOULAOUZIDIS, A. Software for enhanced video capsule endoscopy: challenges for essential progress. *Nature Reviews Gastroenterology & Hepatology* 12, 3 (2015), 172–186.
- [5] IDDAN, G., MERON, G., GLUKHOVSKY, A., AND SWAIN, P. Wireless capsule endoscopy. *Nature* 405 (2000), 417.
- [6] LIU, B.-D., AND HUANG, C.-Y. Design and implementation of the tree-based fuzzy logic controller. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* 27, 3 (1997), 475–487.
- [7] MAMONOV, A. V., FIGUEIREDO, I. N., FIGUEIREDO, P. N., AND TSAI, Y.-H. R. Automated polyp detection in colon capsule endoscopy. *IEEE transactions on medical imaging* 33, 7 (2014), 1488–1502.
- [8] MARSALA, C. *Apprentissage inductif en présence de données imprécises: Construction et utilisation d'arbres de décision flous*. PhD thesis, 1998.
- [9] ROMAIN, O., HISTACE, A., SILVA, J., AYOUB, J., GRANADO, B., PINNA, A., DRAY, X., AND MARTEAU, P. Towards a multimodal wireless video capsule for detection of colonic polyps as prevention of colorectal cancer. In *Bioinformatics and Bioengineering (BIBE), 2013 IEEE 13th International Conference on* (2013), IEEE, pp. 1–6.
- [10] TAJBAKSH, N., GURUDU, S. R., AND LIANG, J. Automated polyp detection in colonoscopy videos using shape and context information. *IEEE transactions on medical imaging* 35, 2 (2016), 630–644.