GRANULOMETRY-BASED DESCRIPTOR FOR PATHOLOGICAL TISSUE DISCRIMINATION IN HISTOPATHOLOGICAL IMAGES

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Abstract

- **Prostate cancer** is one of the types of cancer with the highest incidence in humans. In particular, prostate cancer is the main cause of death from cancer in men over 70 years of age.
- In this work **granulometries are presented** as a novel image descriptor to identify abnormal patterns in the prostatic tissue.
- The morphological alteration suffered by the main structures of pathological glands are registered by the proposed descriptor and achieved in a feature vector.
- A committee of **SVM classifier** is trained to discriminate between healthy and pathological tissue using **45 Whole Slide Images**.
- Accuracy, sensitivity, specificity and **AUC** values higher than **0.89±0.01** demonstrate the effectiveness of the method.

Method

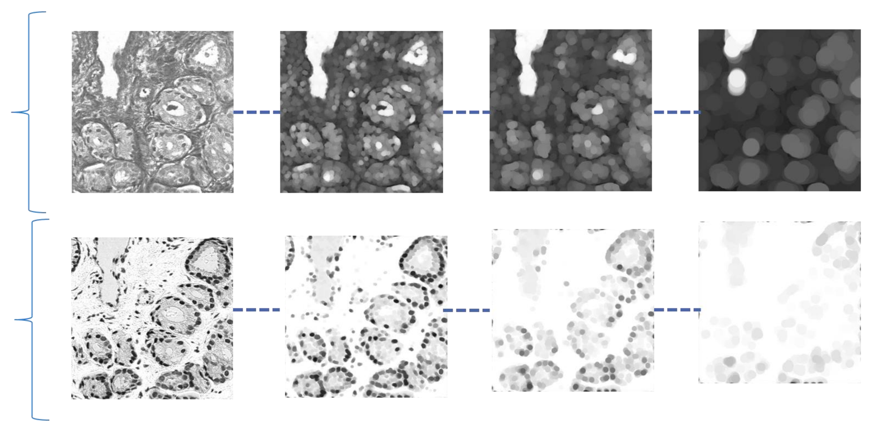
GRANULOMETRY

$$\Pi_\gamma(f) = \{\Pi_{\gamma\lambda}: \Pi_{\gamma\lambda} = \gamma_\lambda(f), \forall\lambda \in [0, s, 2s, \ldots, n_{max}]\}$$

where $\gamma_\lambda(f) = \delta_\lambda(\varepsilon_\lambda(f))$

$$\Pi_\varphi(f) = \{\Pi_{\varphi\lambda}: \Pi_{\varphi_\lambda} = \varphi_\lambda(f), \forall\lambda \in [0, s, 2s, \ldots, n_{max}]\}$$

where $\varphi_\lambda(f) = \varepsilon_\lambda(\delta_\lambda(f))$



$$PS_\Gamma(f, n) = \frac{m\left(\Pi_{\gamma n}(f)\right) - m\left(\Pi_{\gamma n+1}(f)\right)}{m(f)}, \; n \geq 0$$

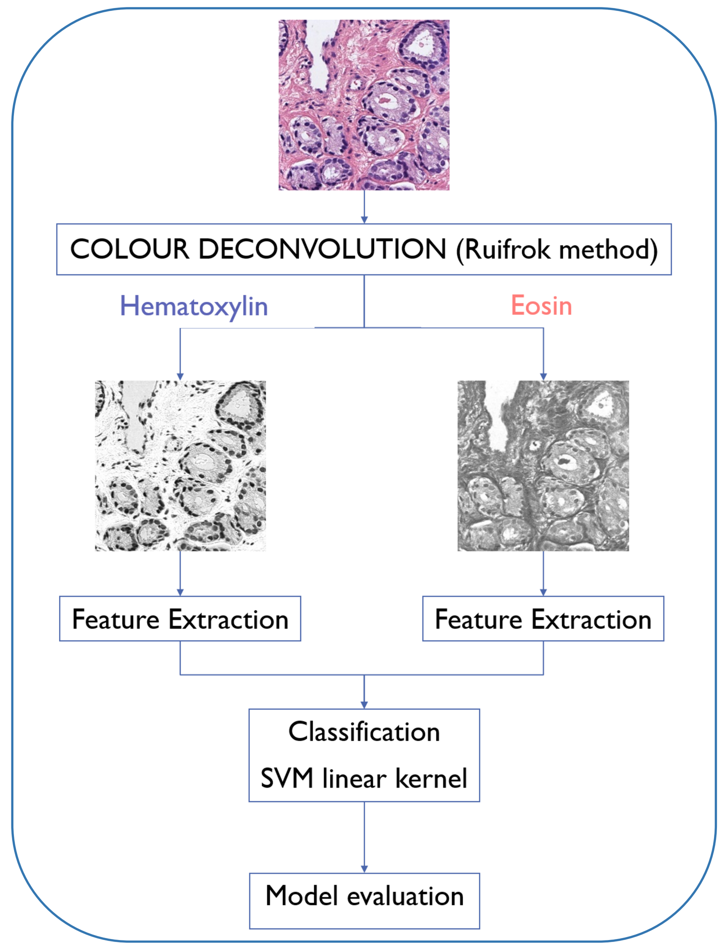
$$PS_\Phi(f, -n) = \frac{m\left(\Pi_{\varphi n}(f)\right) - m\left(\Pi_{\varphi n-1}(f)\right)}{m(f)}, \; n \geq 0$$

GEODESIC GRANULOMETRY

f := Marker image
g := Reference image $\quad (f \leq g)$

$\gamma_i^r(f) = R^\delta_{\gamma_i(f)}(f) \longrightarrow R_g^\delta(f) = \delta_g^{(i)}(f)$, so that $\delta_g^{(i)}(f) = \delta_g^{(i+1)}(f) \longrightarrow \delta_g^{(n)}(f) = \delta_g^{(1)}\delta_g^{(n-1)}(f)$, being $\delta_g^{(1)}(f) = \delta_B(f) \wedge g$

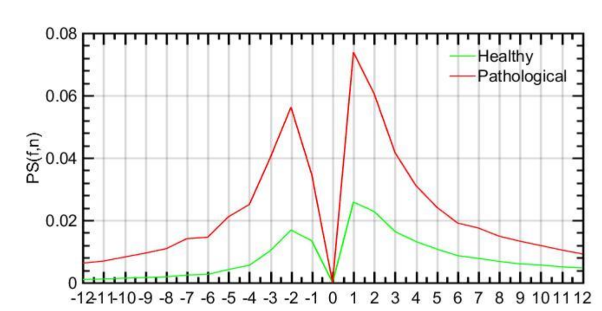
$\varphi_i^r(f) = R^\varepsilon_{\varphi_i(f)}(f) \longrightarrow R_g^\varepsilon(f) = \left[R^\delta_{g^c}(f^c)\right]^c$, being f^c the complement image.

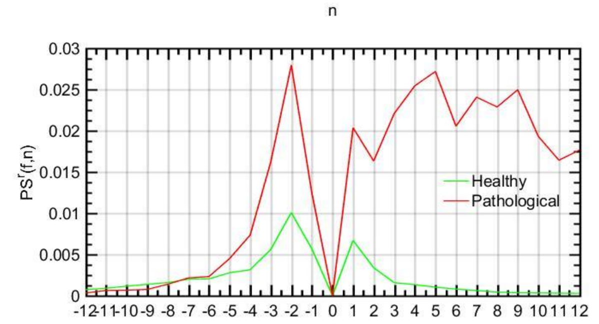


Results

- The method was evaluated using 45 Whole Slide Images (**17 healthy** and **28 malignant**).
- Expert **pathologists manually annotated** relevant **regions** using an online in-house application.
- The **images** were down-sampled from 40x to **10x** and divided in **patches** with an **overlap of 50%**. Different **patch sizes** were tested:
  - 512x512
  - 1024x1024
  - 2048x2048
- **Geodesic granulometry** was compared with baseline **texture descriptors**:
  - Rotational-invariant uniform LBP ($LBP^{riu2}_{P1,R1}$).
  - Rotational-invariant uniform LBP combined with a contrast measure ($LBPV^{riu2}_{P2,R2}$).
  - For the tests $P1 = P2 = 8$ and $R1 = R2 = 1$.

- PS_Φ was computed using the Hematoxylin image with a step for increasing the SE of ***s* =2 and *n*$_{max}$ = 24**.
- PS_Γ is computed using the Eosin image with a step for increasing the SE of ***s* =4** and ***n*$_{max}$ = 48**.
- Signature of PS for healthy and pathological patches:





- ***K*-fold cross-validation** procedure over the whole feature dataset composed. Similar number of instances per fold was obtained: ***K* = 5**.
- The folds present an imbalanced behaviour between healthy and malignant instances: **a committee of *T* SVMs** is learned. **Soft majority voting** was used as the final criterion.
- Each of the *K* committees is **evaluated** by using the **test set**.
- Number of samples for different patch sizes:

	512 x 512	1024 x 1024	2048 x 2048
Healthy	11232	3408	1008
Malignant	1517	663	298

- Results for the best patch size (i.e. 1024 x 1024) for the different evaluated descriptors:

	$LBP^{riu2}_{P,R}$	$LBPV^{riu2}_{P,R}$	Gran.	Geodesic Gran.
Accuracy	0,7124 ± 0,1434	0,6392 ± 0,0973	0,8443 ± 0,0323	**0,9825 ± 0,0155**
AUC	0,8249 ± 0,0975	0,7235 ± 0,0872	0,8876 ± 0,0142	**0,9960 ± 0,0031**
Specificity	0,7048 ± 0,1685	0,6492 ± 0,1603	0,8580 ± 0,0431	**0,9882 ± 0,0160**
Sensitivity	0,7553 ± 0,1232	0,5877 ± 0,2588	0,7737 ± 0,0360	**0,9532 ± 0,0209**
F-score	0,4859 ± 0,1418	0,3351 ± 0,0725	0,6209 ± 0,0455	**0,9482 ± 0,0427**

Conclusions

- In this work, a **novel descriptor to characterize histological images of prostate cancer and differentiate between healthy and pathological regions** was presented.
- The proposed descriptor registers the **granularity** of the elements that compose the prostatic tissue.
- The obtained results showed an **outperformance** of the proposed descriptors with **respect to** baseline **texture descriptors**.
- The optimal results were obtained for the **geodesic granulometric descriptor** using a patch size of **1024 x 1024**.
- In **future work**, the proposed descriptors will be used for classifying different grades of cancer.
- The **annotated database** that is being collected will be **public in the future** to facilitate the comparison of the methods proposed in the scientific community.

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