Material quality assessment of silk nanofibers based on swarm intelligence

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Abstract. In this paper, we propose a novel approach for texture analysis based on artificial crawler model. Our method assumes that each agent can interact with the environment and each other. The evolution process converges to an equilibrium state according to the set of rules. For each textured image, the feature vector is composed by signatures of the live agents curve at each time. Experimental results revealed that combining the minimum and maximum signatures into one increase the classification rate. In addition, we pioneer the use of autonomous agents for characterizing silk fibroin scaffolds. The results strongly suggest that our approach can be successfully employed for texture analysis.

1. Introduction
The silk fibroin is a protein extracted from cocoons of Bombyx mori silkworm. It has been widely used in biomedical applications due to its high capacity to suture tissues, to regenerate bones and its biocompatibility with several types of human cells used in prosthesis [1]. In the last years, researchers have proposed to improve the nanoscale features of silk fibroin by adding glycerol. Though the presence of glycerol can provide better material properties, it also can alter the silk fibroin molecules interactions, damaging the result in its surface. Therefore, texture analysis methods emerge as a powerful tool for determining the suitable concentration of glycerol.

Many methods for texture description have been proposed in the literature. These methods are based on statistical analysis of the spatial distribution (e.g., co-occurrence matrices [2] and local binary pattern [3]), stochastic models (e.g., Markov random fields [4]), spectral analysis (e.g., Fourier descriptors [5], Gabor filters [6, 7]), complexity analysis (e.g., fractal dimension [8]), agent-based model (e.g., deterministic tourist walk [9, 10]). Although there are effective texture methods, they do not capture the richness of patterns of the silk fibroin scaffolds.

In this paper, we present a methodology for classifying surface properties of silk fibroin by means of texture analysis. The texture description approach proposed here is based on the artificial crawler model [11, 12]. We propose a new rule of movement that not only moves artificial crawler agents toward higher intensity, as well as to lower ones. We confirm that this strategy increases the discriminatory power and outperforms the state-of-the-art method.

This paper is organized as follows. Section 2 details the original artificial crawler model. Section 3 presents our approach to characterize textured images. Section 4 discusses the results of the experiments. Finally, conclusions are given in Section 5.
2. The Original Artificial Crawler Model

The first artificial crawler (ACrawler) model was developed in [11, 12]. Let us consider an image that assigns to each pixel \( p = (x_p, y_p) \) an intensity \( I(p) \in [0, 255] \). Each pixel holds a neighborhood set \( \eta(p) = \{ q \mid \text{dist}(p, q) \leq \sqrt{2} \} \), where \( \text{dist} \) is the Euclidean distance.

At each time \( t \), an agent \( i \) is characterized by two attributes: (1) the level of energy \( e_i^t \) and (2) the spatial position in the image \( \rho_i^t \). First, \( n \) agents are born with identical energy \( \epsilon \). Such energy can either wax or wane their lifespan according to energy consumption and influence of the environment. On images, the environment is treated as a 3D surface with different altitudes that correspond to grey values in z-axis of the images. Higher intensities supply nutrients to the agents, while lower altitudes correspond to the land. The algorithm consists of a set of rules:

(i) **Born**: Each agent \( i \) is born with the same energy; \( \forall i, e_i^0 = \epsilon \).

(ii) **Survival threshold**: An agent \( i \) dies if its energy is below the threshold; \( \forall t, i, if e_i^t \leq e_{\text{min}} \) then \( i \) dies.

(iii) **Movement**:

\[
\forall i : e_i^t > e_{\text{min}}, \rho_i^{t+1} = f(\rho_i^t)
\]

\[
f(\rho) = \begin{cases} 
\rho_i^t, & \text{if (a) is satisfied} \\
\rho_{\text{max}}, & \text{if (b) is satisfied} \\
\rho_{m}, & \text{if (c) is satisfied}
\end{cases}
\]

(a) Agents settle down if the grey level of its 8-neighbors are lower than itself.
(b) Agents move if there exist one of its 8-neighbors (\( \rho_i^{\text{max}} \)) with higher intensity.
(c) If there exist more than one neighbor with higher intensity, an agent moves to the pixel that already was occupied (\( \rho_m^t \)).

(iv) **Energy consumption**: Each time \( t \) consumes one unity of energy; \( \forall i : e_i^t > e_{\text{min}}, e_i^{t+1} = e_i^t - \epsilon_{\text{unity}}.\)

(v) **Law of the jungle**: An agent with higher energy eats up another with lower one:

\[
\forall i, j : e_i^{t+1} = e_i^{t+1}, e_{\text{max}} \{ e_i^t, e_j^t \} = \max \{ e_i^t, e_j^t \}.
\]

(vi) **Gain of energy**: It up to dates the energy absorption from the environment, where \( \lambda \) is a rate of absorption over the pixel \( I(\rho_i^t) ; \forall i, e_i^{t+1} = e_i^t + \lambda I(\rho_i^t) \).

(vii) **Limit of energy**: It bounds the maximum energy \( e_{\text{max}} \); \( \forall t, i, e_i^{t+1} \geq e_{\text{max}}, e_i^{t+1} = e_{\text{max}} \).

To quantify the multi-agent system, a curve of live agents at each time is obtained:

\[
\varphi = [\psi(0), \psi(1), \ldots, \psi(t_{\text{max}})]
\]

where \( \psi(t) \) is the number of live agents at time \( t \) and \( t_{\text{max}} \) is maximum iteration.

3. A Novel Approach with Artificial Crawler to Texture Analysis

The artificial crawler model described above consists of moving agents to a neighbor pixel with the highest intensity. Despite the promising results, this idea does not extract all the richness of textural pattern. Our approach differs from the original ACrawler model in terms of movement: each agent is not only able to move to the higher altitudes as well as to lower ones. It allows the model to extract the details present in peaks and valleys of the images.

First, the agents move to higher intensities as the original artificial crawler method. Thus, the artificial crawlers are performed using this rule and the curve \( \varphi_{\text{max}} \) is obtained. Throughout the paper, this rule of movement will be referred as \( \text{max} \). We can observe that the original
artificial crawler method only models the peaks of a textured image. To obtain a robust and effective texture representation, we propose to move artificial crawlers toward lower intensities – this rule of movement will be referred throughout the paper as to \( min \). In our approach, artificial crawlers are randomly placed in the image with initial energy \( \epsilon \). Then, the conditional movement step is modified as follows:

(a) Agents settle down if the grey level of its 8-neighbors are higher than itself.

(b) Agents move to a specific pixel if there exist one of its 8-neighbors \( \rho_{min}^t \) with lower intensity.

(c) If there exist more than one neighbor with lower intensity, an agent moves to the pixel that already was occupied \( \rho_m^t \).

The multi-agent systems using the rule of movement \( min \) is characterized as the original method by using the number of live agents at each time. Considering that now we have two rules of movement, the final feature vector of our approach is composed by the concatenation of \( \varphi_{max} \) and \( \varphi_{min} \) according to:

\[
\varphi = [\varphi_{max}, \varphi_{min}]
\] (2)

4. Experimental Results

In this section, we demonstrate the effectiveness of our approach. We first outline details of the experimental setup, and then, experiments carried out on two datasets are discussed: Brodatz and silk fibroin.

For classification, we adopted the Linear Discriminant Analysis (LDA) using ten-fold cross validation [13]. The number of agents placed on the pixels of the image was initial set to 1000 with a coverage rate of 10%, varying from 1000 to 35000. In our experiments, all agent was born with an initial energy \( \epsilon \) of 10 units and the loss for each iteration consumes 1 unit of energy. The absorption rate was set to 0.01 in terms of the current pixel. For the survival threshold and the upper bound of energy were set to 1 and 12 units, respectively.

**Experiment 1:** First, we perform an analysis of our method on the Brodatz dataset (40 classes with 10 samples) [14]. The results of the proposed method are compared with existing methods in Table 1. It is observed that the our method outperforms the state-of-the-art. The highest classification rate of 98.25\% (±1.69) was obtained by our method, which is followed by a classification rate of 95.25\% (±3.43) obtained by the Gabor filter, one of the most traditional texture analysis method.

**Experiment 2:** In this experiment, we present a comparative study of our approach to assess the quality of the silk fibroin scaffolds. The potential of the silk fibroin is enhanced by including glycerol solutions (usually 0\% to 10\% with step of 2.5\%) during scaffold formation [1]. The silk fibroin dataset contains 5 classes with 10 samples. Figure 1 shows three samples for each concentration. In the silk fibroin dataset, our method achieved highest classification rates when compared with traditional texture analysis methods. The experimental results, presented in Table 1, shows that our method achieved a classification rate of 96\% (±8.43). These experimental results indicate that our method is consistent and can be applied in real-world applications.

5. Conclusion

In this paper we presented a novel approach based on artificial crawler for texture classification. We have demonstrated how the feature vector can be improved by combining \( min \) and \( max \) curves, instead of using only the strategy for the maximum of intensity of the pixels. Although traditional methods of texture analysis have provided satisfactory results, the approach proposed here has proved to be superior for characterizing textures from a popular benchmark and from the silk fibroin scaffolds analysis.
Figure 1. Samples for each glycerol concentration. The first column corresponds to 0% of concentration, the second 2.5%, and so on up to 10%.

Table 1. Experimental results for texture methods in the Brodatz and Silk Fibroin datasets.

| Method                        | Brodatz       | Silk Fibroin  |
|-------------------------------|---------------|---------------|
| Fourier descriptors [5]       | 86.50 (±6.58) | 78.00 (±22.01)|
| Co-occurrence matrices [2]    | 91.25 (±2.65) | 94.00 (±9.66) |
| Original artificial crawler   | 93.00 (±5.50) | 84.00 (±15.78)|
| Gabor filter [7]              | 95.25 (±3.43) | 62.00 (±19.44)|
| Proposed method               | **98.25 (±1.69)** | **96.00 (±8.43)** |

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