



Healthy and unhealthy red blood cell detection in human blood smears using neural networks

Hany A. Elsalamony^{a,b,*}

^a Mathematics Department, Faculty of Science, Helwan University, Cairo, Egypt

^b Computer Science & Information Department, Arts & Science College, Sattam University, Saudi Arabia

ARTICLE INFO

Article history:

Received 1 December 2015

Received in revised form 26 January 2016

Accepted 27 January 2016

Available online 1 February 2016

Keywords:

Healthy/unhealthy RBC detection and counting

Circular hough transforms

Segmentation

Neural network

ABSTRACT

One of the most common diseases that affect human red blood cells (RBCs) is anaemia. To diagnose anaemia, the following methods are typically employed: an identification process that is based on measuring the level of haemoglobin and the classification of RBCs based on a microscopic examination in blood smears. This paper presents a proposed algorithm for detecting and counting three types of anaemia-infected red blood cells in a microscopic coloured image using circular Hough transform and morphological tools. Anaemia cells include sickle, elliptocytosis, microsite cells and cells with unknown shapes. Additionally, the resulting data from the detection process have been analysed by a prevalent data analysis technique: the neural network. The experimental results for this model have demonstrated high accuracy for analysing healthy/unhealthy cells. This algorithm has achieved a maximum detection of approximately 97.8% of all cells in 21 microscopic images. Effectiveness rates of 100%, 98%, 100%, and 99.3% have been achieved using neural networks for sickle cells, elliptocytosis cells, microsite cells and cells with unknown shapes, respectively.

© 2016 Published by Elsevier Ltd.

1. Introduction

The general components of human blood are plasma, white blood cells (WBCs), red blood cells (RBCs) and platelets. RBCs comprise approximately 40% of blood volume. WBCs are smaller in volume but larger in size than RBCs. Plasma is the fluid component that contains melted salts and proteins. Platelet cells are similar particles but are smaller than WBCs and RBCs (Xia and Wu, 2015; Biradar et al., 2015; Deligiannidis and Arabnia, 2014).

Anaemia is a type of red blood cell disorder that is usually caused by a lack of mineral iron in the blood. The human body needs iron to produce the iron-rich protein haemoglobin, which helps red blood cells carry oxygen from the lungs to the remainder of the body (Elsalamony, 2014; Das et al., 2013). This disease occurs when the blood has a lower than normal number of red blood cells (RBCs) or an insufficient amount of haemoglobin. RBCs are located inside the large bones of the body in the spongy marrow. The main function of marrow is to renew red blood cells, which continuously replaces old red blood cells. Normal RBCs die after they have lived in the bloodstream for 120 days. Their jobs include carrying oxygen and

removing carbon dioxide (a waste product) from the body (Lam, 2015).

RBCs are disc-shaped and can easily move through blood vessels. Elliptocytosis is a well-known type of anaemia. Historically, this disease was described in 1904 and recognized as a hereditary condition in 1932. The medical determination of hereditary elliptocytosis is difficult. The incidence of this disease ranges between three and five cases per 10,000 in the USA, whereas an estimated 60–150 cases per 10,000 of African and Mediterranean natives and 1500–2000 per 10,000 cases of Malayan natives have been documented (Lee and Chen, 2014).

In sickle-cell anaemia, which is a serious disorder, the body creates a crescent shape of red blood cells. These sickle cells contain abnormal haemoglobin, which is referred to as sickle haemoglobin or haemoglobin S; it helps cells to develop a crescent shape. The absence of a polar amino acid encourages the noncovalent combination of haemoglobin in a low-oxygen environment, which distorts the red blood cells into a sickle shape and decreases their elasticity. Biochemically, the low-oxygen environment causes a chain of neighbouring haemoglobin molecules to hook together and block blood flow in the blood vessels of the limbs and organs, which become rigid and polymerized. Low blood flow can cause pain, organ damage, and increase the probability of disease. These cells fail to return to their normal shape when oxygen is restored and fail to deform as they pass through nar-

* Correspondence to: Mathematics Department, Faculty of Science, Helwan University, Cairo, Egypt.

E-mail addresses: h.salamony@yahoo.com, hanyelsalamony@gmail.com

row vessels, which causes blockages in the capillaries ([2015b]). Abnormal sickle cells usually die after approximately ten to 20 days. Bone marrow cannot renew red blood cells fast enough to replace dying red blood cells (Thirusittampalam et al., 2013). No cure exists for sickle cell anaemia. However, treatments can help to release pain and improve the complications of this disease. In addition, sickle-cell anaemia is common in people whose families derive from Mediterranean countries, Africa, South, or Central America, especially Panama, the Caribbean islands, Saudi Arabia, and India. In the United States, the disease derived from 70,000 to 100,000 people, primarily African Americans. The diagnosis of sickle cell anaemia is dependent on blood test analyses that can detect sickle cells (2015a).

In the same context, microsities consist of small red blood cells. The most common causes of microcytic anaemia are iron deficiency and the thalassemia trait. The ability to distinguish microsities is very important for providing genetic counselling and preventing unnecessary and damaging iron therapy in thalassemia carriers. One of the simplest and most powerful discriminant functions is the ratio of microcytic cells to normal red blood cells (Urrechaga et al., 2015). The average size of a normal red blood cell is a mean corpuscular volume (MCV) in the range of 80–100 fL; smaller cells (<80 fL) are described as microcytic. In microcytic anaemia, red blood cells usually appear paler than usual (James, 2015). In addition, the measure that represents the amount of haemoglobin per unit volume of fluid inside a cell is referred to as the mean corpuscular haemoglobin concentration (MCHC); a normal cell has a MCHC range of approximately 320–360 g/L or 32–36 g/dL. Therefore, anaemia in this category is classified as microcytic anaemia (Weng et al., 2011). Fig. 1 illustrates the difference in the shapes of normal RBCs, microsities, sickle cells, elliptocytosis cells, platelets and some unknown-shaped cells, which appeared in the smear. The importance and danger of anaemia have prompted research on resistance and diagnosis. A diagnosis begins by discovering and counting the number of unhealthy cells in blood compare to the number of healthy cells in blood. This paper provides a proposed algorithm to detect healthy/unhealthy blood cells (elliptocytosis, sickle cells, microsities and unknown-shaped) based on the detection of their shapes using the circular Hough transform (CHT), watershed, and morphological tools. Therefore, the cells' data variables, including area, convex area, perimeter, eccentricity, solidity, and ratio (refer to Eqs. (1) and (2)), which can be extracted from the detection process by a neural network to obtain an appropriate diagnosis (Chaudhuri and Bhattacharya, 2000; Freeman, 1991).

The remainder of the paper is organized as follows: Section 2 focuses on related studies. The proposed algorithm is discussed in Section 3, and the experimental results that demonstrate the effectiveness of the model are detailed in Section 4. Section 5 presents the materials and devices employed in the experimental results. The conclusions in this paper are discussed in Section 6.

2. Related studies

In recent years, research on the detection of red blood cells and the determination of illnesses by utilizing image processing has increased. In 2010, Hirimutugoda and Wijayarathna (2010) displayed a technique to distinguish thalassemia and malarial parasites in blood test images that were procured from light-magnifying instruments and explored the likelihood of fast and precise computerized determination of red blood cell disorders. To assess the accuracy of the classification of therapeutic image patterns, they prepared two neural network models (three and four layers) composed with image examination strategies using morphological elements of RBCs. The three layers yielded the best execution with an error of $2.74545e^{-005}$ and an 86.54% accurate identifica-

tion rate. The three prepared layers of an ANN comprised the most recent discovery classifier to detect infections.

In December 2012, Das et al. (2013) introduced a methodology that employs machine learning techniques for characterizing RBCs in anaemia based on microscopic images of peripheral blood smears. First, to reduce the unevenness of background illumination and noise, they preprocessed peripheral blood smear images based on a geometric mean filter and the technique of grey world assumption. Second, a watershed segmentation technique was applied to erythrocyte cells. Unhealthy RBCs, such as sickle cells, echinocyte cells, teardrop cells, and elliptocytosis cells, and healthy cells were classified based on their morphological shape changes. They observed that the logistic regression classifier exhibited better performance when a small subset of features were employed using information gain measures. They achieved the highest prediction in terms of total accuracy by 86.87%, a sensitivity of 95.3%, and a specificity of 94.13%.

In January 2013, Taherisadr et al. (2013) which presented an automated red cells analysis and classification from developed individual specimens. This method was based on shape features and an internal central pallor configuration of red cells and their circularity using a decision logic. Red blood cells were classified into 12 categories to diagnose blood disorders such as iron deficiency anaemia, the anaemia of chronic diseases, β -thalassemia trait, sickle cell anaemia, haemoglobin C disease, intravascular haemolysis, hereditary elliptocytosis, hereditary spherocytosis and megaloblastic anaemia due to folic acid deficiency. In this method, they described some thresholds to classification with high efficiency in a coordination of results. They investigated morphological points of view and calculated parameters and thresholds to obtain the quantitative results of cell areas and diameters.

In July 2013, Mushabe et al. (2013) introduced an algorithm after recognizing and tallying red blood cells (RBCs) and parasites to perform a parasitemia estimation. Morphological operations and a histogram-based edge were employed to identify red blood cells. They utilized boundary curvature calculations and Delaunay triangulation to split overlapped red blood cells. A Bayesian classifier with RGB pixel values were employed as elements to order the parasites. The outcomes demonstrated 98.5% affectability and 97.2% specificity for identifying tainted red blood cells.

In 2014, Mukherjee (2014) assessed the morphometric components of placental villi and vessels in preeclampsia and typical placenta. The study included light microscopic images of placental tissue regions of 40 preeclampsia and 35 normotensive pregnant women. The villi and vessels were depicted from preprocessing and division of these images. He applied principal component analysis (PCA), Fisher's linear discriminant analysis (FLDA), and hierarchical cluster analysis (HCA) to perceive placental (morphometric) features, which are basic features in microscopic images. He detected five tremendous morphometric features (>90% total discrimination accuracy) perceived by FLDA, and PCA detected three critical principal components, which cumulatively elucidated 98.4% of the aggregate variance.

In 2014, Lee and Chen (2014) introduced a neural network model with a classifier, which utilize the visual information obtained from the images of red blood cells images to determine if a red blood cell is standard or odd. They clustered the visual components into two essential parts—shape cluster groups and texture cluster groups—depending on the component properties. The input feature clusters were considered using parallel and coarse construction with input various data layers. Their trial results demonstrated imperative change and exactness in the proposed structure, which was distinguished from the single information layer classifier with element selection algorithms.

In 2015, Yi et al. (2015) proposed a three-dimensional characterization strategy for consequently identifying the morpho-

Download English Version:

<https://daneshyari.com/en/article/1588708>

Download Persian Version:

<https://daneshyari.com/article/1588708>

[Daneshyari.com](https://daneshyari.com)