

Computer Aided Evaluation (CAE) of Morphologic Changes in Pigmented Skin Lesions

Maria Rizzi¹(✉), Matteo D'Aloia², and Gianpaolo Cice²

¹ Politecnico di Bari - Dipartimento di Ingegneria Elettrica e dell'Informazione, Bari, Italy

maria.rizzi@poliba.it

² MASVIS SRL, Conversano, Italy

{matteo.daloia,gianpaolo.cice}@masvis.com

Abstract. Mole pattern changes are important elements in detecting cancerous skin lesions, the early stage detection is a key factor to completely cure the pathology. In this paper, an automatic system for mole-tracking is indicated. The method presented is been realized as a mobile app and can be used to perform periodically a careful self-examination of their pigmented skin lesions. The implemented method receives in input two segmented images of the same pigmented skin lesion corresponding to the actual image and to the image before the last period under test. The method performs image matching and changes evaluation adopting a three stage artificial neural network and provides as output a risk indicator related to the morphology changes of the skin lesion.

Keywords: Smart health · Healthcare · Neural network · Skin lesion · Computer aided detection · Computer aided evaluation · Border detection · Edge detection · CAD · CAE

1 Introduction

Smart and healthy cities share common characteristics as they move from focusing their investment on traditional, physical infrastructures to more emphasis on digital infrastructures, including information and communication technologies. Milestones are the creation of networked and data driven cities able to keep citizens more informed, engaged and empowered. Digital infrastructures enable citizens to actively contribute to sustainable development, as well as, to self-manage their own health [1].

The objectives of smart and healthy cities are to seek improvements in safe, effective, efficient and patient-centered health and wellness services through innovations in computers, information science and engineering. Therefore, the adoption of information technologies and management systems for health care improvement is very important. For this reason, efforts mainly focus on computerization of hospitals and medical institutions [2].

Researchers look for innovative solutions and new technologies both for making the quality of patient care better and for reducing the cost of care through an early disease detection and diagnosis. Computer aided health systems allow acquisition, transmission, processing, storage, retrieval and analysis of various health and biomedical information.

Health service quality depends on information quality in hospital complex or in diagnostic center. Efficient hospital information system should be able to manage all patient specific data and to automated detect disease specific information for helping physicians in decision-making process within therapeutic algorithms. Moreover, in smart city achieving, databases of public hospitals and diagnostic centers should be connected together in such a way as to guarantee an effective and efficient service toward citizens. Therefore, interoperability of devices and systems is necessary. The adoption of a common standard for data facilitates interoperability of medical imaging equipment by specifying a set of media storage services, a file format and a medical directory structure.

The convergence of various information and communication technologies (i.e. smart systems, cloud computing, advanced sensing and data analysis techniques) provides potentialities for delivering automated, intelligent, and sustainable healthcare services [3].

In medical imaging, the accurate diagnosis and/or assessment of a disease depends on both image acquisition and image interpretation. Therefore, medical image interpretation process can benefit from computer technology [4, 5]. In particular, Computer Aided Detection (CADe), Computer Aided Diagnosis (CADx) and Computer Aided Evaluation (CAE) systems are becoming important tools in supporting physicians for neoplastic pathology detection and prevention [6, 7]. In particular it has been demonstrated that information content of slides of pigmented skin lesions is not modified by the digitalization process [8].

Since changes in pigmented skin lesions are important for early disease detection, dermatologists makes nevo photography to study the evolution. Lesion manual inspection and matching is subjective and tedious. For this reason, an automatic matching between lesions is useful for physicians.

In this paper, a Computer Aided system for tracking pigmented skin lesions is indicated. For the method implementation, mole macroscopic images acquired with standard cameras are used. In fact, the adoption of commercially available photographic cameras is quite common in skin lesion inspection systems, particularly for telemedicine purposes. Moreover, the implemented method can run on smartphones of the last generation which provide high resolution cameras and innovative operating systems.

In this paper, after a brief review of the most recent methods indicated in literature for the tracking of skin moles, the implemented tool is presented and its performance is evaluated. Moreover, some conclusions are drawn out.

2 Prior Researches and Adopted Approaches

As a consequence of the increase of skin tumor incidence, the interest for computer-aided skin lesion inspection and characterization has grown during the last years. In fact, the World Health Organization has evaluated a grow of about 30% over the last 10 years; worldwide each year, 132,000 subjects develop melanoma, the most common skin cancer [9].

For skin cancer early detection, mole tracking and mapping is useful.

The system indicated in [10] adopts, as input, a pair of skin back images of the same subject captured at different times. A set of anatomical landmarks are detected using a pictorial structure algorithm. Lesions that are located within the polygon defined by landmarks are identified and their anatomical spatial contexts are encoded by landmarks. Then, these lesions are matched by labelling an association graph using a tensor based algorithm. A structured support vector machine is employed for the matching.

Voronoi cells are used in [11] to measure the similarity between melanomas in successive dermatoscopy images. The melanoma registration is reduced to a bipartite graph matching problem. A minimum weight maximum cardinality matching is employed for finding the global correspondences between images.

A method for finding corresponding moles in patient skin back images at different scanning times is indicated in [12]. To calculate mole normalized spatial coordinates, a template is defined for human back and then mole matching across images is modeled as a graph matching problem. Algebraic relations between nodes and edges in the graphs are induced in the matching cost function.

In [13], pigmented skin lesion matching problem is formulated as a relaxed labeling of an association graph. In this graph labeling problem, each node represents a mapping between a pigmented skin lesion from one image to a pigmented skin lesion in the second image. Optimal labels are obtained optimizing a high order Markov Random Field energy (MRF). A novel entropy energy term encouraging solutions with low uncertainty is proposed in the method. By interpreting the relaxed labeling as a measure of confidence, authors leverage the high confidence matching to sequentially constrain the learnt objective function defined on the association graph.

Matching probabilities of the edges of two graphs representing the spatial distribution of two pigmented skin lesion sets is evaluated in [14]. Pointwise probabilities is extracted using marginalization matrix of computed pairwise matching.

In [15] effectiveness in matching and identifying lesions in pairs of skin images of point pattern correlation, 2-point geometrical transformation, and 3-point geometrical transformation are investigated. These techniques view spots in each image as a point pattern to be matched from image to image. Experiments indicate that the 3-point transformation algorithm performs the best overall.

3 Adopted Method

In the proposed system an Artificial Neural Network (ANN) is employed for the tracking of pigmented skin lesions. In fact, ANN is robustness since it provides less operation load and has more advantageous for reducing the noise effect [16]. Moreover, ANN is more useful, because multiple inputs and outputs can be used during the stage of training [17]

ANNs are computational models based roughly on the human neural structure. They can be defined by a stimulus response transfer characteristics, called activation function, that maps input space into a specified output space [18, 19, 20].

The most commonly used network architecture consists of a number of connected nodes (neurons) which are arranged in a hierarchical sequence of different layers (input, hidden and output). Each node in a layer receives an input from all the nodes in the preceding layer, and transmits output to the nodes of the succeeding layer. The connections between nodes are weighted, putting different strengths on the information exchange between two nodes.

The nonlinear characteristic exhibited by neurons is represented by a activation function. Neuron output is computed as the weighted sum of the input signals, transformed by the activation function. Therefore, neuron output signal is given by the following relationship:

$$O = f \left(\sum_{j=1}^n w_j p_j \right) \quad (1)$$

where (p_1, p_2, \dots, p_n) is the neuron input vector, (w_1, w_2, \dots, w_n) the weight vector and $f(\cdot)$ the activation function.

Having defined both a network architecture and a training set of input patterns, the set of weights determines the network output for each input patterns. Error between the obtained network output and the expected target output defines a potential multi-modal response surface over a multidimensional hyperspace having the dimensions coincident with the number of weights.

The most used method for finding weight set is the Back Propagation (BP) procedure that is essentially a gradient method. The BP learning process operates in small iterative steps: an example case is applied to the network, and the network produces an output based on the current state of its weights. This output is compared to the target output and a mean-squared error signal is calculated. The error value is then propagated backwards through the network and small changes are made to weights in each layer. The weight changes are calculated for error signal reduction. The whole process is repeated for each of the example cases and the cycle is repeated until the overall error value drops below some pre-determined threshold. At this point the network has learned the problem "well enough": the network will never learn exactly the ideal function, but rather it will asymptotically approach an approximation of it.

The application of ANNs to nonlinear signal processing is a challenge that requires considerable engineering judgment. ANN design involves raw data pre-processing, feature extraction from the pre-processed data, selection of network model and type, network testing and evaluation. The design process is typically a complex iterative and interactive problem-specific task. The choice of both network model and type is based on precise requirements of the problem. Different ANN models and types having different features may offer special advantages for particular applications.

4 The Proposed CAE System

Images of skin lesion acquired with standard cameras represent the input of the implemented system. Macroscopic images can be segmented adopting one of the method indicated in literature, than are processed to calculate images feature. The paper aim is the accuracy in evaluating the lesion border changes with the passing of time.

In order to perform the tracking of pigmented skin lesions, an ANN has been selected as classifier for its characteristic to enhance desired responses and reduce irrelevant and unwanted responses if noisy and imprecise nonlinear data are given.

A suitable ANN classifier is designed for the mapping of skin lesions. As it is well known that any function with a finite number of discontinuities can be well approximated by a three-layer neural network with sufficient neurons in the hidden layer[21], the implemented classifier is a feed-forward ANN composed of three layers. The classifier contains 6 neurons in the input layer and 1 neuron in the output layer. In order to achieve the best performance, various ANN architectures are used which differed on the neuron number inside the hidden layer(fig.1).

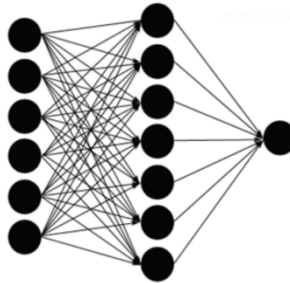


Fig. 1. The ANN architecture

Three features for image are selected for the classification process, that are: the ratio of the lesion maximum diameter to the lesion minimum diameter, the lesion compactness and eccentricity.

The maximum diameter is defined as the maximum distance between two pixels of the segmentation and the minimum diameter is the maximum distance that exists between two pixels within a segmented lesion projected on the perpendicular to the maximum diameter

Lesion compactness is defined as the ratio of the squared lesion perimeter to the lesion area and it represents the roughness of an object boundary relative to its area.

Lesion eccentricity is related to the ellipsoid hull and it is defined as: $(L_1^2 - L_2^2)^{1/2}/L_1$ where L_1 and L_2 are the major and the minor semiaxis, respectively.

Since the ANN has to map two images of the same lesion captured at different times, the vector formed by the twelve feature values (six for each image) represents an input pattern while the class to which the lesion changes belong represent the output.

A back propagation procedure is adopted for the training phase. The error is measured with the mean square error function.

During the training stage, features computed for all the images are fed into the network. Once weights and biases of neurons associated with network are initialized, the network is trained to produce expected outputs, that is 1 for appreciable changes and 0 for no appreciable changes.

In the training process, weights between neurons were adjusted iteratively so that differences between output values and target values are minimized. The training phase is terminated when 50 iterations have been performed.

5 Simulation Results

For the method implementation and validation, 200 macroscopic lesion images (100 pairs) provided from databases of various dermatology local centers are utilized. For a correct performance evaluation, the training data are not used during the testing stage. In particular 80 images (40 pairs) are adopted for the network training while 120 images (60 pairs) represent the method test bench.



Fig. 2. One of the image pairs used as test bench

In fig.2 one of the image pair used as ANN input are shown.

The method achieves an average accuracy value in detecting lesions for which morphologic changes warrant particular attention equal about to 82%. For the accuracy evaluation, opinions of three different dermatologists are considered as a ground truth.

The best performance is obtained adopting an ANN classifier with 7 neurons in the hidden layer (fig.3).

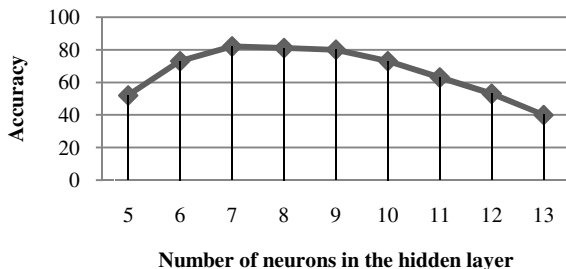


Fig. 3. Method accuracy vs number of neurons in the hidden layer

6 Conclusion

The last century has produced a proliferation of innovations in health care industry aimed at enhancing life expectancy, quality of life, diagnostic and treatment options, as well as efficiency and cost effectiveness of healthcare system. Therefore, discovery of some critical pathologies in their early stage represents a healthcare benefit in fact it is useful to reduce mortality and morbidity rates, to shorten illness duration, to improve the quality of care and to limit the decay of a person functions which corresponds to increase in life expectancy. In particular, the interest of biomedical scientific community for computer aided skin lesion inspection and characterization has been increased during the last years.

There is an important clinical need to follow changes in the number of moles and their appearance (size, color, texture, shape) in images from two different times.

In this paper, a computer tracking system for mapping of pigmented skin lesions adopting macroscopic images captured with standard cameras, is indicated. The method can be adopted independently from the procedure used for image lesion segmentation or image border detection. For this reason the presented tool could be implemented as the last stage of a mole tracking system which receives as inputs mole images segmented adopting any method indicated in literature.

The method simplicity and the adoption of standard camera images as inputs make the system particularly appropriate to be used in telemedicine and to run on smart-phones. Therefore, the implemented system can be used as assistive devices by patients for self-manage their own health (personal health) and by primary care physicians during routine office visits.

References

1. Solanas, A., Patsakis, C., Conti, M., Ioannis, S.V., Ramos, V., Falcone, F., Postolache, O., Pérez-Martínez, P.A., Di Pietro, R., Perrea, D.N., Martínez-Ballestéc, A.: Smart Health: A Context-Aware Health Paradigm within Smart Cities. *IEEE Commun. Mag.* **52**, 74–81 (2014)
2. Rizzi, M., D'Aloia, M., Castagnolo, B.: Review: Health Care CAD Systems for Breast Microcalcification Cluster Detection. *J. Med. Biol. Eng.* **32**, 147–156 (2012)
3. Rizzi, M., Maurantonio, M., Castagnolo, B.: A Wireless Sensor Network for Security Systems Adopting the Bluetooth Technology. *WSEAS Transaction on Circuits and Systems* **5**, 652–657 (2006)
4. Rizzi, M., D'Aloia, M., Castagnolo, B.: High Sensitivity and Noise Immune Method to Detect Impedance Cardiography Characteristic Points Using Wavelet Transform. *J. of Appl. Sci.* **9**, 1412–1421 (2009)
5. Rizzi, M., D'Aloia, M., Castagnolo, B.: A New method for ICG characteristic point detection. In: 11th Int. Conf. on Bio-inspired Syst. and Signal Process., pp. 244–249. INSTICC, Portugal (2008)
6. Rizzi, M., D'Aloia, M., Castagnolo, B.: A Fully Automatic System for Detection of Breast Microcalcification Clusters. *J. Med. Biol. Eng.* **3**, 181–188 (2010)
7. D'Aloia, M., Rizzi, M., Di Bari, P.A.: Second Opinion System for Microcalcification Diagnosis. *World Appl. Sci. J.* **23**, 289–295 (2013)

8. Perednia, D.A., Gaines, J.A., Butruille, T.W.: Comparison of the Clinical Informativeness of Photographs and Digital Imaging Media with Multiple-Choice Receiver Operating Characteristic Analysis. *Arch. Dermatol.* **131**, 292–297 (1995)
9. Fondazione melanoma. <http://www.fondazionemelanoma.org/melanoma-epi.php>
10. Mirzaalian, H., Lee, T.K., Hamarneh, G.: Skin Lesion Tracking Using Structured Graphical Models. *Med. Image Anal.*, April 2015
11. Huang, H., Bergstresser, P.: A hybrid technique for dermatological image registration. In: 7th IEEE International Conference on Bioinformatics and Bioengineering, pp. 1163–1167. IEEE Press, Boston (2007)
12. Mirzaalian, H., Hamarneh, G., Lee, T.K.: A graph-based approach to skin mole matching incorporating template-normalized coordinates. In IEEE Conference on Computer Vision and Pattern Recognition, pp. 2152–159. IEEE Press, Miami (2009)
13. Mirzaalian, H., Lee, T.K., Hamarneh, G.: Uncertainty-based feature learning for skin lesion matching using a high order MRF optimization framework. In: Ayache, N., Delingette, H., Golland, P., Mori, K. (eds.) MICCAI 2012, Part II. LNCS, vol. 7511, pp. 98–105. Springer, Heidelberg (2012)
14. Mirzaalian, H., Hamarneh, G., Lee, T.: Graph-based approach to skin mole matching incorporating template-normalized coordinates. In: IEEE Conference on Computer Vision and Pattern Recognition, pp. 2152–2159. IEEE Press, Miami (2009)
15. Perednia, D.A., White, R.G.: Automatic registration of multiple skin lesions by use of point pattern matching. *Comput. Med. Imaging Graph.* **16**, 205–216 (1992)
16. Egmont-Petersen, M., de Ridder, D., Handels, H.: Image Processing with Neural Networks – A Review. *Pattern Recogn.* **35**, 2279–2301 (2002)
17. Becerikli, Y., Demiray, H.E.: Alternative Neural Network Based Edge Detection. *Neural Information Processing Letters and Reviews* **10**, 193–199 (2006)
18. Rizzi, M., D’Aloia, M., Guaragnella, C., Castagnolo, B.: Health Care Improvement: Comparative Analysis of Two CAD Systems in Mammographic Screening. *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans* **42**, 1385–1395 (2012)
19. Rizzi, M., D’Aloia, M., Castagnolo, B.: A Supervised Method for Microcalcification Cluster Diagnosis. *Integr. Comput-Aid. E.* **20**, 157–167 (2013)
20. Rizzi, M., D’Aloia, M.: Computer Aided System for Breast Cancer Diagnosis. *Biomed. Eng-App. Bas. C.* **26**, 14500331–14500338 (2014)
21. Zheng, L., He, X.: Edge detection based on modified BP algorithm of ANN. In: Pan- Sydney Area Workshop on Visual Information Processing, pp. 119–122. Australian Computer Society Press, Sydney (2003)