Computers in Biology and Medicine 52 (2014) 88–95

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/cbm

Phase-based probabilistic active contour for nerve detection in ultrasound images for regional anesthesia

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ARTICLE INFO

Article history:
Received 21 June 2012
Accepted 2 June 2014

Keywords:
Ultrasound images
Medical image processing
Active contours
Probabilistic learning
Monogenic signal
Regional anesthesia

ABSTRACT

Ultrasound guided regional anesthesia (UGRA) is steadily growing in popularity, owing to advances in ultrasound imaging technology and the advantages that this technique presents for safety and efficiency. The aim of this work is to assist anaesthetists during the UGRA procedure by automatically detecting the nerve blocks in the ultrasound images. The main disadvantage of ultrasound images is the poor quality of the images, which are also affected by the speckle noise. Moreover, the nerve structure is not salient amid the other tissues, which makes its detection a challenging problem. In this paper we propose a new method to tackle the problem of nerve zone detection in ultrasound images. The method consists in a combination of three approaches: probabilistic, edge phase information and active contours. The gradient vector flow (GVF) is adopted as an edge-based active contour. The phase analysis of the monogenic signal is used to provide reliable edges for the GVF. Then, a learned probabilistic model reduces the false positives and increases the likelihood energy term of the target region. It yields a new external force field that attracts the active contour toward the desired region of interest. The proposed scheme has been applied to sciatic nerve regions. The qualitative and quantitative evaluations show a high accuracy and a significant improvement in performance.

1. Introduction

Regional anesthesia (RA) is a technique used to inhibit sensation in a particular region of human body, such as an arm or a leg. It consists in distributing the anesthetic product around the nerve structures to eliminate sensitivity and mobility. The main advantage of regional anesthesia is that it immobilizes a selected region of the body while having little effect on other parts, such as respiratory functions. This enables fast recovery and reduces the side effects when compared to general anesthesia. The benefit of RA is particularly pronounced for pain management during surgery and other medical procedures [1]. The key requirement for successful regional anesthesia is localization of the nerve block in order to ensure optimal distribution of the local anesthetic around nerve structures [2]. The conventional method of nerve localization uses nerve stimulation, which presents a high risk of nerve trauma. The use of ultrasound (US) imaging for RA is steadily increasing: its advantages over conventional techniques are significant, since it allows direct ultrasonographic guidance of the needle to the nerve zone [3–5].

The nerve structure includes several types of tissues. A single nerve fiber is surrounded by endoneurium. A group of nerve fibers forms a nerve fascicle. Each nerve fascicle is surrounded by perineurium. Nerve fascicles together form a nerve which is surrounded by epineurium. Nerve tissues have different behaviors under ultrasound waves. Nerve fibers themselves do not reflect any ultrasound (hypoechoic) so they appear dark. Only the connective tissue surrounding the nerve fibers, the fascicles and the nerve (Epineurium) reflects ultrasound (hyperechoic) and thus appears bright [4]. Fig. 1 shows an example of the nerve anatomy and its cross-section visualized by ultrasound imaging.

The use of ultrasound guided regional anesthesia (UGRA) in daily clinical practice requires a high degree of training and practical skills to identify the nerve block and steer the needle to it [2]. This can limit the development and the generalization of the practice of UGRA. There are two critical steps in UGRA: the recognition of anatomical structures (i.e. target nerves, vascular structures, etc.) and needle tracking during insertion. The aim is to develop an assistance system that can handle these critical issues, hoping to spark a shift towards easier practice of regional anesthesia under sonographic guidance. This work focuses on

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http://dx.doi.org/10.1016/j.compbiomed.2014.06.001
0010-4825/

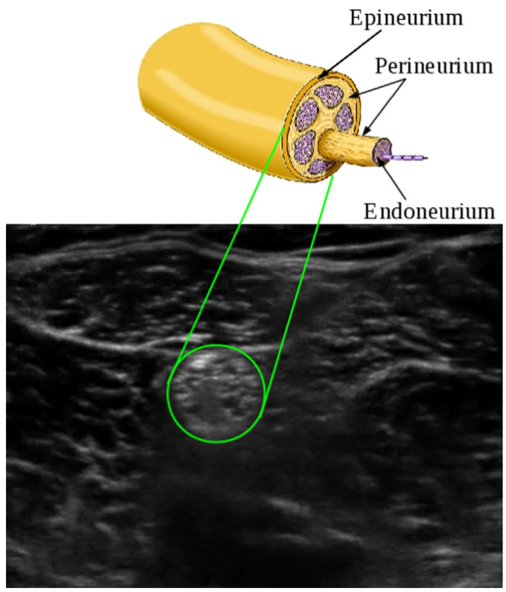

Fig. 1. Popliteal nerve anatomy and appearance in the ultrasound image.

the first phase, in particular the automatic detection of nerve blocks in the ultrasound images.

Ultrasound imaging is among the hardest imaging modality upon which to perform segmentation and recognition, due to the artifacts such as attenuation, speckle, shadows, and signal dropout. Various segmentation methods for ultrasound images have been developed [6]. Active contour models are among the most successful techniques, and have been extensively used for this application showing useful properties for region detection and noise robustness [7–13].

Active contours were first proposed by [14]. Curves or surfaces are associated with an energy function; the minimization of the energy function allows convergence to an object boundaries. Active contour models can be split into two main categories depending on the image characteristics: edge-based models and region-based models. Edge-based models use the boundary information, generally provided by the gradient operator, to guide the curve evolution, while region-based models use region information such as texture, color, etc. However, traditional active contour models have not achieved a good segmentation performance, due to the poor quality of the ultrasound images. Different strategies have been proposed in an attempt to improve active contour models by introducing new criteria such as robust edge detection [15], probabilistic approach [11], etc. For instance, phase-based analysis can significantly enhance local properties in ultrasound images such as the edges [16–19]. This approach has been successfully applied to segmenting echocardiography images [20,21,15]. Probabilistic and statistical approaches combined with active contours have been also proposed, showing useful properties for ultrasound segmentation [22–25,11,13]. These methods have been used in various medical contexts such as cardiovascular disease, breast tumors, prostate cancer, etc. where the regions to be detected are either hypoechoic or hyperechoic. The nerve presents a specific pattern that combines both hypoechoic and hyperechoic structures, which is not salient amid the different tissues (arteries, muscles, etc.) [2].

To deal with nerve detection in ultrasound images, it is important to combine low level processing and high level analysis of the image information. Indeed, one can take advantage of both concepts: the learning approach and phase-based analysis. The learning approach with a probabilistic model can handle nerve zone identification using textural features. However, the boundary precision will be affected since a large pixel neighborhood is required to capture the texture information. Fuzzy boundaries are not desirable for RA applications because the needle should be as close as possible to the nerve contour for delivery of the anesthetic. The phase-based approach is a highly appropriate technique to detect strong edges in the ultrasound images. Combining the two concepts will improve the segmentation procedure, because both operate in different ways to reduce the segmentation noise and constrain the active contours to converge to the desired regions of interest.

In this paper we propose a new method that combines a phase-based approach for robust edge detection and a probabilistic model to generate a reliable external force for the active contour model. In this work we use the gradient vector flow (GVF) model [26]. The GVF model possesses several desirable properties, such as convergence to boundary concavities that do not need to be initialized close to the boundary. Owing to its efficiency, the GVF method has been developed and adapted to several problems [27–30]. Our aim is to strengthen the GVF external force field near the nerve region and weaken it in the other parts of the image, making the dynamic curve move toward the region of interest. To build the probabilistic model, the first step consists in nerve texture characterization using a Gabor filter. Then, the mixture model is built from the nerve region using the textural features. This model is utilized to compute the probability of each pixel in the different images, indicating which pixels are most likely to belong to the nerve zone. To segment the regional anesthesia US images efficiently, each value of the probability map is considered as a weighting coefficient of the vector flow obtained with phase-based edge detection and the GVF procedure. This makes it possible to emphasize the nerve block and allows rapid convergence to its boundaries.

The paper is organized as follows: the following section describes the background methods, Section 3 presents the proposed scheme, Section 4 reports our experiments and results, and Section 5 concludes the paper.

2. Background

This section describes the three main background methods used to develop our technique, namely gradient vector flow, the local phase approach and Gabor filter.

2.1. Gradient vector flow (GVF)

Parametric active contours consist of internal and external forces that steer a dynamic curve $\mathbf{x}(c) = [x(c), y(c)]$, $c \in [0, 1]$ with the well-known snake equation [14]:

$$E_{AC} = \frac{1}{2}\int_0^1 \alpha|\mathbf{x}'(c)|^2 + \beta|\mathbf{x}''(c)|^2 \, ds + \int_0^1 \varepsilon(\mathbf{x}(c)) \, ds \quad (1)$$

where α and β are positive weighting parameters. The first term is referred to as the internal energy, which controls the smoothness of the curve x, while the second term is referred to as the external energy, which attracts the curve x toward the object boundary. This energy plays an important role in guiding the contour to the correct region of interest. In traditional active contour models this is defined as $\varepsilon(x, y) = -g(x, y)$ that is,

$$g(x, y) = |\nabla(G_\sigma(x, y) * I(x, y))|^2 \quad (2)$$

where $I(x, y)$ is the image intensity function and $G_\sigma(x, y)$ is a 2-D Gaussian filter with standard deviation σ. However, this external energy has a limited capture range and poor convergence to a complex shape boundary. Gradient vector flow (GVF) was proposed to solve these problems by changing the external forces