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SYMMETRY AND APPEARANCE BASED AUTOMATED DETECTION OF SALIENT ANATOMICAL REGIONS IN ULTRASOUND

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Abstract— **In this paper we present a method for automated detection of enclosed anatomical regions in ultrasound images by utilizing the coarse shape symmetry as well as relative homogeneity of their sonographic appearance. The proposed method comprises of two steps: First, local phase based filtering [2] is used to detect points in the image which are roughly positioned along the axes of spatial symmetry with respect to structures around them. Secondly, the sonographic 'appearance' and location of these points is used to define a distance-map on the image, which is supplied to a simple fast-marching algorithm in order to provide the final feature detections. The method is robust to ultrasound speckle and works well with or without specialized pre-processing (e.g. speckle-reduction filtering). We illustrate the proposed method with qualitative results on *in-vivo* Ultrasound images.**

I. INTRODUCTION

Over the last decade, radically improving image quality and reduced cost has led to Ultrasound becoming a popular clinical imaging modality for almost all relevant medical specialities and its use at the *point-of-care* has been rapidly increasing. We believe that automated analysis, detection and quantification would go a long way in improving the imaging work-flows, reduce subjectivity in assessment and ultimately improve clinical outcomes. Unlike other conventional imaging modalities such as Computed Tomography (CT), Magnetic Resonance (MR), etc, Ultrasound is challenging for automated image analysis due to the characteristic speckle patterns, non-linear contrast changes and commonly used non-uniform acquisition geometry (curved arrays). In this paper we present a technique for completely automated and robust detection of salient enclosed features (e.g. blood vessels, gall-bladder, etc) as illustrated in Figure 1, which may be extremely valuable for clinical applications like: automated image enhancement, region-of-interest generation for (say) Doppler processing, feature based automated registration, etc. Most well-known edge-detectors (e.g. [3]) generate cluttered edge-maps on ultrasound images due to the characteristic speckle patterns present in ultrasound imagery (see Figure 1). Authors in [5] have proposed an information theoretic measure for detecting edges which is more robust

Fig. 1. Visually salient anatomical regions: original image (left), Canny [3] edge-detector output (center) and output of the proposed approach (right).

to speckle. The approach proposed in [4] utilizes a spatial network of perceptually salient[1] points in the image which are used to prune noisy edges. In the proposed approach, we focus more on detecting salient regions as opposed to detecting edges in order to reduce the amount of spurious detections generally reported by edge based methods.

A. PHASE-CONGRUENCE AND PHASE-SYMMETRY

Local phase computations have been used by authors in [8], [9] etc, where the phase information is explicitly used to delineate the edges of anatomical structures and to design penalty or energy terms using the local-phase in order to segment anatomical structures of interest. Other approaches like [7] use *phase-congruency* (see [1]) for detecting salient edges. In this paper we utilize the concept of *phase-symmetry* proposed by [2] where the phase-symmetry measure computes image intensity based symmetry *"in exclusion of everything else"*. Figure 2 illustrates the differences between phase-congruence and phase-symmetry measures computed from an ultrasound image. Before we proceed, we must

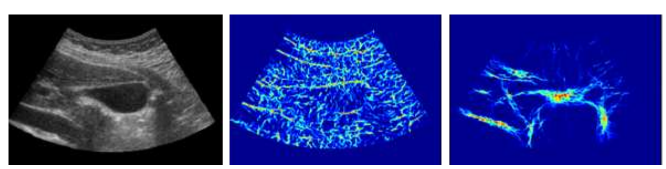

Fig. 2. Phase congruence vs. phase symmetry: the original ultrasound image is shown (left) with the phase congruence map (center) and the phase symmetry map (right). The color-map indicates high-values with red and low values with blue.

emphasize that in regards to local-phase, the approach pro-

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[1]This notion favors smooth long curves with constant curvature.

posed in this paper uses the concept of *symmetry* and not *congruence* (which is commonly used for edge detection). We employ local phase computations for detecting interior points (as opposed to boundary points) of anatomical structures with homogeneous sonographic appearance. The identification of these interior (approximate symmetry axis) points allows automatic *initialization* of the segmentation. The rest of the paper is structured as follows: Section II describes the symmetry and appearance based detection in more detail. We illustrate the effectiveness of the proposed approach through results on multiple (> 10) real patient images and also discuss limitations and future directions in Section III.

II. DETECTING SYMMETRIC STRUCTURES USING PHASE AND APPEARANCE

We use *Log-Gabor* wavelet filters to perform the analysis of a given image I. As in [2], denoting the even-symmetric and odd-symmetric wavelets at a scale n by ${M_n}^e$ and ${M_n}^o$ respectively, we can write the equation for the response of the filters as:

$$[e_n(x), o_n(x)[= [< I(x), {M_n}^e >, < I(x), {M_n}^o >] \quad (1)$$

whereby, the amplitude and phase of the transform at a scale n can be given by:

$$A_n(x) = \sqrt{e_n(x)^2 + o_n(x)^2} \quad (2)$$

$$\Phi_n(x) = atan2(e_n(x), o_n(x)) \quad (3)$$

Given Equations 1, 2 and 3, the symmetry measure is then computed as [2]:

$$Sym(x) = \frac{\Sigma_n \left[e_n(x) - o_n(x)\right] - T}{\Sigma_n A_n(x) + \epsilon} \quad (4)$$

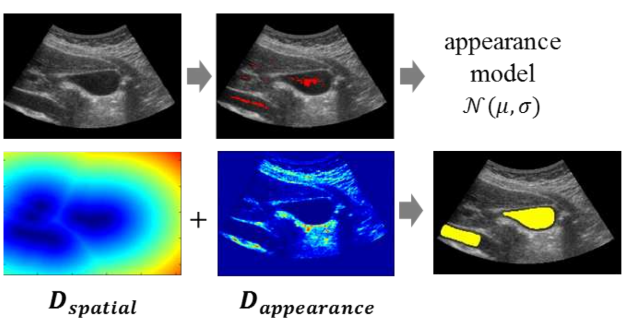

Fig. 3. Proposed approach: local phase symmetry peaks (top-center) are detected from the original image (top-left). The pixels in the vicinity of these peaks are used to generate an *appearance-model* of the anatomical region. A spatial distance map (bottom-left) computed relative to the symmetry peaks is coupled with the appearance-distance (bottom-center) to provide a feature image for a fast-marching ([6]) based segmentation (bottom-right).

Figure 3 provides an overview of the proposed approach. The phase symmetry measure computed using Equation 4 is thresholded to approximate points along the axes of intensity-symmetry of structures in the image. A prior knowledge about the likely appearance of the structures of interest can then be used to further prune these regions. Nominal amount of morphological pre-processing is performed to generate a final symmetry-peaks mask I_{peak} (top-center in Figure 3). The appearance of the pixel blobs in I_{peak} can then be modelled using a Mixture-of-Gaussians (MoG) distribution. A Euclidean distance map $D_{spatial}$ can be generated with respect to the symmetry peaks in I_{peak} and the MoG appearance model is used to generate an appearance distance map $D_{appearance}$. A combination of the spatial and appearance distances is then used as a speed image for the standard Fast-Marching algorithm [6] where the symmetry peaks in I_{peak} provide the initial seed points for the segmentation.

III. RESULTS AND DISCUSSION

Figure 4 provides a large collection of real patient images which were used to validate the proposed approach. It can be observed that the visually salient structures in the image are captured well by the algorithm. We do not provide particular quantification with segmentation approaches because segmentation is not the primary goal of the approach proposed here. The output of our algorithm should be used to provide an initialization for more sophisticated applications such as: image enhancement, region-of-interest specification, registration, etc. The entire algorithm took a few seconds to run on a 512x512 image on a Intel i5 processor with 4GB memory using non-optimized experimental code (in C++ using the ITK© library). From our experiments, the approach was quite robust and relatively insensitive to parameters. Images with multiple structures with large variations in size were challenging to process because of the difficulty in automated assessment of the right parameters to capture all structures in the image. Further experiments in these directions will be reported elsewhere.

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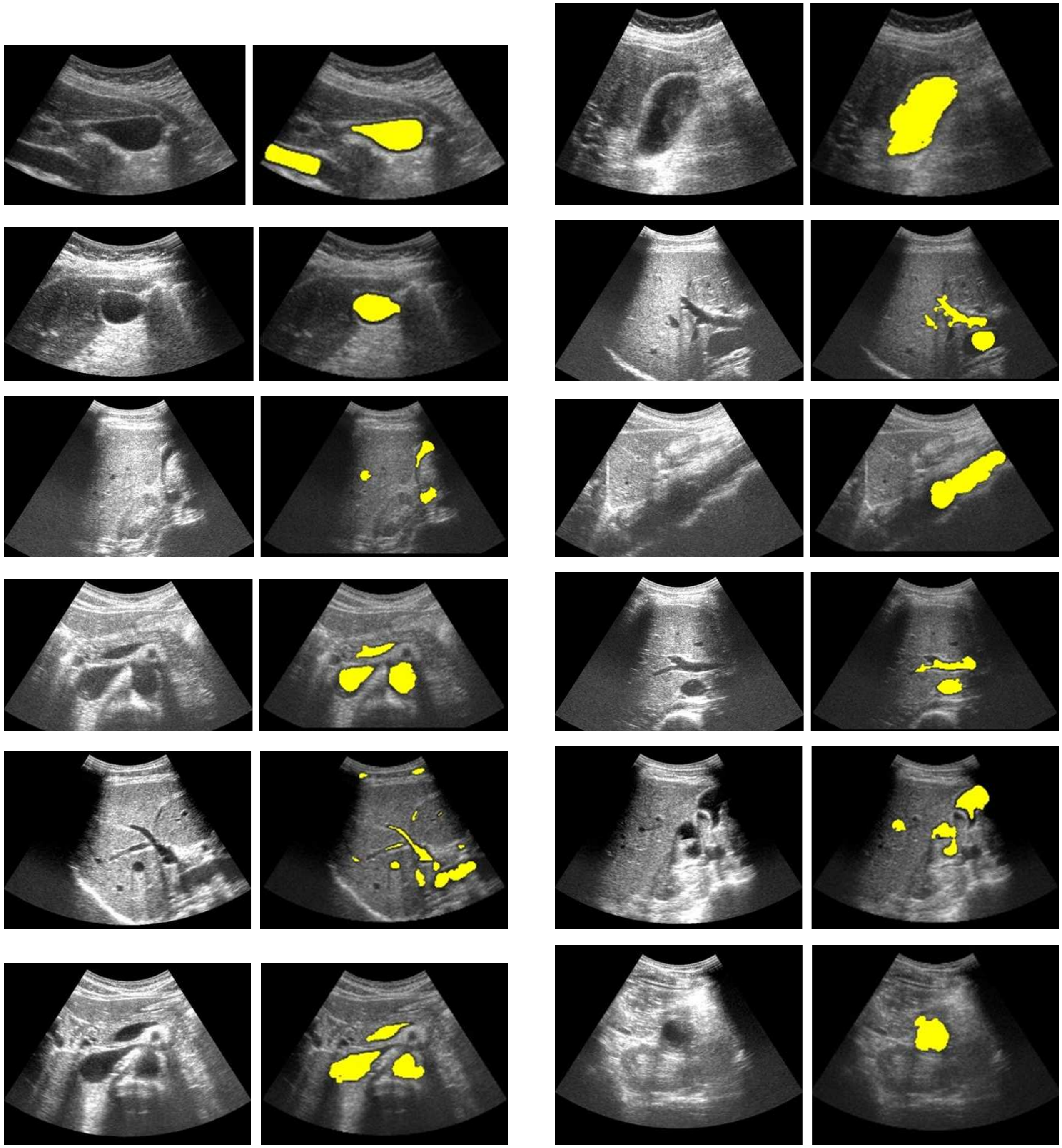

Fig. 4. A collage of results from the proposed approach. Results are shows as image pairs with the original (left) and output (right) where the detected regions are overlaid in yellow.