Semi-automatic method for delineation of midbrain in transcranial ultrasound images

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Introduction. Transcranial sonography (TCS) is a method, which was recently applied as a diagnostic tool for supporting a clinical diagnosis of Parkinson's disease (PD). Initial results revealed that TCS has the potential to become a powerful tool in diagnostics of various neurological movement disorders [1-3]. However, scanning of the deep brain structures through the skull bone inevitably causes specific problems with image quality. A spatial resolution of TCS images is much lower compared with the ultrasound images obtained during scanning of the soft tissue. The structures of an interest (midbrain, mesencephalic substantia nigra) sometimes are hardly recognizable in the obtained B-mode images due to missing or diffused boundaries. The limited spatial resolution of images makes the diagnostics of neurological disorders dependent upon the experience of the examiner. Computer assisted segmentation of TCS images could reduce inter-observer and intra-observer variability, but there is no validated efficient technique for the segmentation of the brain structures in TCS images. Only a few computer-based attempts to perform the segmentation of midbrain structures could be found [4, 5].

The aim of this paper is to present new method developed for semi-automated segmentation of midbrain combining principle of statistical shape modelling and local phase accumulation based boundary detection strategy.

Materials and Methods. The principle of statistical shape model (SSM) introduced by T. Cootes in 1995 [6] was employed for semi-automatic delineation of midbrain in TCS image. The goal of SSM is to create parameterized model of the form $\mathbf{x} = \mathrm{M}(\mathbf{b})$, which is used to generate new shapes $\mathbf{x}$ similar to examples in the original training set [7]. The area of interest in transcranial ultrasound images has a characteristic shape feature. Frequently the expression "butterfly-shaped midbrain" (see Fig. 1 (a)) is used. With respect to that the SSM of midbrain contour could be created.

The SSM is constructed having s sets of training shapes $\mathbf{x}_i$ aligned in a common coordinate frame. Any shape in a training set could be defined as a sum of mean shape and a plausible deviation of shape controlled by vector $\mathbf{b}$:

$$\mathbf{x} \approx \bar{\mathbf{x}} + \mathbf{Pb}, \tag{1}$$

where $\mathbf{x} = (x_1,\ldots, x_n, y_1,\ldots, y_n)^{\mathrm{T}}$ the vector of coordinates of shape (contour), n – number of contour points, $\bar{\mathbf{x}}$ - mean shape obtained averaging s training shapes, $\mathbf{P} = (\mathbf{p}_1|\mathbf{p}_2|\mathbf{p}_3|\ldots|\mathbf{p}_t|)$ is a matrix of t eigenvectors, obtained applying Principal

Component Analysis (**PCA**) to the data, number t – depends on predefined number of eigenvalues. Model points in an image frame are defined as:

$$\mathbf{x} = T(\bar{\mathbf{x}} + \mathbf{Pb}), \tag{2}$$

where T is scale (s_x, s_y), rotation (Θ) and shift (x_t, y_t) transform. For one point (x_i, y_i) T can be defined as:

$$T\begin{pmatrix} x_i \\ y_i \end{pmatrix} = \begin{pmatrix} x_t \\ y_t \end{pmatrix} + \begin{pmatrix} s_x \cos\theta & -s_x \sin\theta \\ s_y \sin\theta & s_y \cos\theta \end{pmatrix}\begin{pmatrix} x_i \\ y_i \end{pmatrix}. \tag{3}$$

The final contour of region of interest is found by solving constrained optimization problem. The region boundary coordinates vector **g** is found by fitting SSM points to a target points in an image frame by minimizing squared sum of distances between model and target points:

$$\mathbf{g} = \min\left(\sum (\mathbf{y} - T(\bar{\mathbf{x}} + \mathbf{Pb}))^2\right), \tag{4}$$

where **y** - coordinate vector of target points in an image. The constraints for scale, shift, rotation and shape transform was adjusted thus ensuring that spatially variant realistic shape will be generated. Following optimization constraints were applied: s_x, $s_y = 0.8 – 1.2$, $|\Theta| = \pi/8$, $|x_t|$, $|y_t| = 20$ pixels (size of the pixel 0.421 mm), $|b_i| < 4\sqrt{\lambda_i}$ (λ_i – i-th eigenvalue). Sixty contours of midbrain manually delineated by experts were used for the model construction (other 142 were used for testing). The threshold $\Sigma\lambda_i > 0.98$ was selected, thus ensuring that 98% of variance is controlled by the model.

The procedure of target points **y** detection in an image could be explained in three stages. Firstly, mean contour ($\bar{\mathbf{x}}$) of midbrain was manually placed (initialization) in the image frame (see Fig. 1 (b)) adjusting scale and orientation as well as possible**.** Secondly**,** pixel intensity $I(i,j)$ projections into normals $I_i(\mathbf{n}_i)$ were computed, equally in the both directions of $\bar{\mathbf{x}}$, where $i = 1 \ldots n$ (see Fig. 1 (c), (d)). The intensity was projected using cubic interpolation method. All the projections were organised efferently, thus preserving crossing of midbrain (darker area in an image) – surrounding tissue (brighter area) boundary in the same manner. Lastly, approximate midbrain boundary (target) points in each intensity projection are detected thus forming a vector **y**. Approximate midbrain boundary points was detected applying local phase analysis based detection strategy. P. Kovesi [8] showed that image features such as step edges and intensity ridges can be detected via local phase congruency in different scales of image. The ideal boundary in ultrasound image can be modelled as step edge between the two structures with different acoustic impedance. It is known that all Fourier components are in phase [8, 9] in case of step edge (0 – positive edge or π – negative) and intensity ridge (π/2), meanwhile phase deviates otherwise. Therefore these structures can be recognized by detecting the similarity of local phase in different scales (frequency subbands). The local frequency information was obtained applying log-Gabor filter bank [8, 9]. The log-Gabor quadrature filter in frequency domain is defined:

$$G(\omega) = \exp\left(- \frac{\log(\omega/\omega_0)^2}{2(\log(\kappa/\omega_0))} \right), \tag{5}$$

where κ – parameter of the bandwidth of a filter, ω_0 – center frequency of a filter.

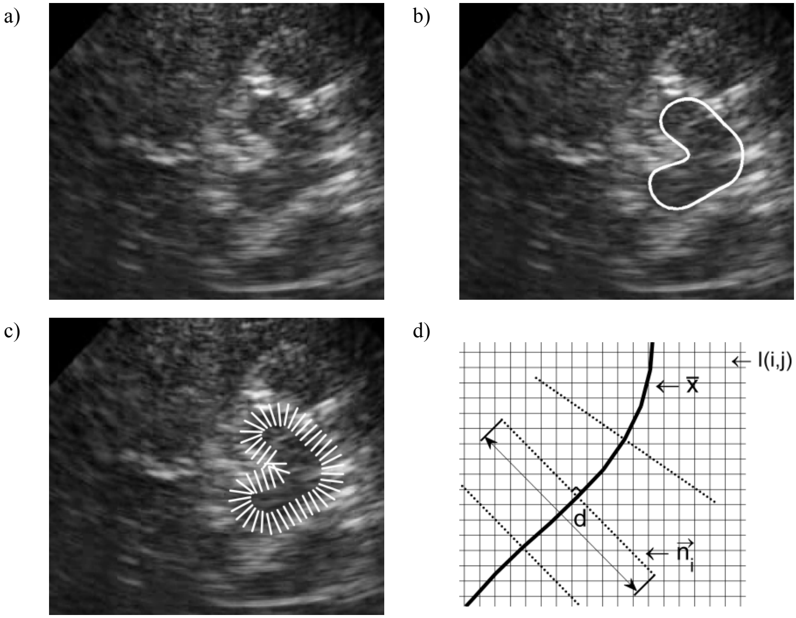


Fig. 1. (a) An example of TCS image, (b) the image with manually placed mean contour $\bar{\mathbf{x}}$, (c) The image with normals computed around the initial contour; (d) the sketch of intensity projection computation.

Local phase angle estimate at predefined scale j of i-th intensity projection was obtained by:

$$\phi_j(\mathbf{n}_i) = \tan^{-1}(F^{-1}(I(\omega, \mathbf{n}_i) \cdot G_j(\omega))), \tag{6}$$

where, F^{-1} – inverse Fourier transform, $I(\omega,\ \mathbf{n}_i)$ – Fourier transform of i-th intensity projection, j=1...s, s – number of scales. The local phase similarity between different scales was evaluated using local absolute phase accumulation (*LPA*) based indicator [10]. LPA of i-th projection:

$$LPA_i = \frac{1}{s} \sum_{j=1}^{s} \left| \phi_j(\mathbf{n}_i) \right|. \tag{7}$$

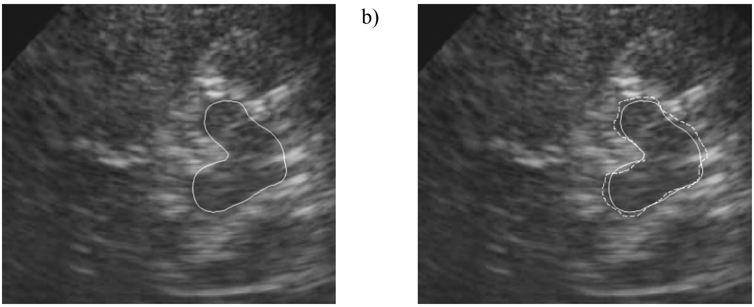
All the projections were computed in the same manner therefore the task was to detect the positive step edge according to LPA_i estimate. The absolute value of local phase angle smooth the phase characteristics but both the positive edge and the negative edge now correspond to π radians, so additional sign function of local phase was applied for detection only the positive edge. Finally i-th target point in a vector **y** is found by:

$$\mathrm{y}_i = \arg\max\left[LPA_i \cdot \left((-1) \cdot \mathrm{sgn}\left\{ \frac{1}{s} \sum_{j=1}^{s} \phi_j(\mathbf{n}_i) \right\} \right) \right]. \quad (8)$$

The parameters of the SSM based method was adjusted as follows: points in a model n = 50, number of scales s = 50, the bandwidth of a filter κ/ω_0 = 0.55, wavelength of a filter λ = 5 – 54 pixels (ω_0 = 1/λ), length of normals d = 8 mm.

Results. An example of result of segmentation of midbrain is presented in Fig. 2. (a). The contour obtained by proposed method was compared to manual delineation by four different metrics: 1) Hausdorff distance (*HD*); 2) mean squred error (*MSE*); 3) *DICE* coefficient, and 4) Bland Altman (*B-A*) plot. Averaged results (mean±sd) of 142 cases: *HD* = 3.36±0.88 mm, *MSE* = 2.18±0.55 mm, *DICE* = 0.88±0.03. The extracted contour compared to manual annotation is shown in Fig. 2. (b).

a) b)



c)

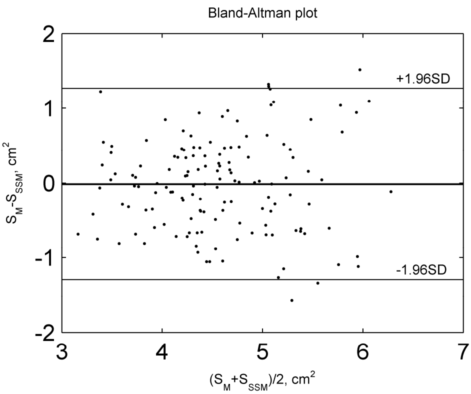


Fig. 2. Results of segmentation of midbrain: (a) contour obtained by proposed method; (b) comparison of the extracted contour and annotation; (c) Bland-Altman plot of differences of the midbrain areas (manual vs. SSM).

The *HD*, *RMSE*, *DICE* and Bland-Altman analysis (mean difference - 0.0854 cm^2) indicates that the method is comparable to manual annotations. However the limits of agreement of B-A plot are quite wide (in some cases the difference exceeds a surely unacceptable 1 cm^2).

Discussion and Conclusions. An efficient technique for midbrain segmentation was proposed. The combination of experience based shape model and intensity-amplitude invariant edge detector was applied for extraction of fuzzy boundaries of midbrain in TCS image.

The robustness of the model ensures that contour will converge to the boundary even if part of the target points will be detected wrongly when there is no expressed positive edge in the intensity projection.

Visual evaluation of extracted contours showed that: 1) in the worst cases (according B-A) the image quality was extremely low, 2) segmentation quality is strongly dependent on initialization (manual placement of mean contour). This shortcoming could be solved employing automated midbrain detection algorithm, but scale, shift and rotation invariant method is needed. Furthermore it should be mentioned that reliability of manual annotations in some cases raises doubts.

All the parameters (variance threshold in a model, number of points in a modelled contour, length of normals, and number of log-Gabor filter scales) of the method were adjusted manually for the best average performance. Phase localisation can suffer increasing the filter scale (the wavelength) because if the filter is too large few edges can be fused and location of the maximal mean phase shifted.

Acknowledgement. This work was sponsored by Lithuanian Science Council in the frame of National Health Program of Chronic Non-Infectious Diseases, the project "Application of transcranial ultrasound for diagnostics of neurodegenerative diseases". No. of contract: LIG-28/2010.

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The aim of this paper is to present new method developed for semi-automated segmentation of midbrain in low quality transcranial ultrasound images. The combination of experience based shape model and intensity-amplitude invariant edge detector was applied for extraction of fuzzy boundaries of midbrain in TCS image. Averaged results of 142 cases obtained comparing contours extracted by proposed method and annotations: Hausdorff distance – 3.36±0.88 mm, mean squared error – 2.18±0.55 mm, Dice coefficient – 0.88±0.03. The results indicate that efficient technique for midbrain segmentation was proposed.