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Adaptive segmentation algorithm based on level set model in medical imaging

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ABSTRACT

For image segmentation, level set models are frequently employed. It offer best solution to overcome the main limitations of deformable parametric models. However, the challenge when applying those models in medical images stills deal with removing blurs in image edges which directly affects the edge indicator function, leads to not adaptively segmenting images and causes a wrong analysis of pathologies wich prevents to conclude a correct diagnosis. To overcome such issues, an effective process is suggested by simultaneously modelling and solving systems' two-dimensional partial differential equations (PDE). The first PDE equation allows restoration using Euler's equation similar to an anisotropic smoothing based on a regularized Perona and Malik filter that eliminates noise while preserving edge information in accordance with detected contours in the second equation that segments the image based on the first equation solutions. This approach allows developing a new algorithm which overcome the studied model drawbacks. Results of the proposed method give clear segments that can be applied to any application. Experiments on many medical images in particular blurry images with high information losses, demonstrate that the developed approach produces superior segmentation results in terms of quantity and quality compared to other models already presented in previeous works.

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1. INTRODUCTION

In the field of imaging, the process of image segmentation involves splitting image into areas sharing the same properties. The task of image segmentation is very important in process of medical image treatment or analysis such as in computer-aided diagnostic (CAD) systems. Several CAD systems that work on medical images [1] have successfully applied segmentation. In the traditional way, clustering approaches, such fuzzy mean, are used to achieve image segmentation [2] and many manually created low-level features, like pixel value distribution and gradient histogram, can be clustered using a genetic algorithm [3]. In image segmentation, probabilistic techniques are also frequently employed [4]–[6]. In [7] a framework for regression segmentation is proposed is proposed for detection of vascular abnormalities in cardiac magnetic resonance imaging by delimiting the two ventricles' boundaries. Among the primary difficulties in using automatic medical image segmentation for magnetic resonance imaging (MRI) and computed tomography (CT) scans is the defect with imaging process that frequently lead to inconsistencies brightness and contrast levels as well as low sharpness of image of borders. On the other hand, deformable active contours are an efficient tool for image segmentation and pattern recognition [8]–[11] and represents explicitly the object's shape and boundary, they combine many souhaible characteristics. Level set models are also known as geometric deformable models, rovide better solutions to overcom the main drawbacks of parametric deformable models.

The idea of the level set method is based on the initialization of a two dimensional (2D) closed curve, or a three-dimensional surface this curve has a potential that allows it shifting at a given speed perpendicular to itself [12]. The level set approach is employed in image processing as a segmentation tool through the evolution of a contour utilizing the image properties. We represent an interface C known in this approach as a level set function of higher dimension. We define this level set over the rest of the image as the signed distance function from the zero level set. Conventionally, this distance takes positive values for pixels inside C and negative values for pixels outside C. Unfortunately, the level set function frequently develops irregularities during its evolution and thus causes numerical errors which reaches the stability of the level set evolution, a numerical solution, known as reinitialization [13], [14], is introduced to overcome this undesirable situation and maintain stable level set evolution, but the problem that arises when applying reinitialization is how and when it ought to be carried out which affects the numerical precision. In [15], distance regularized level set evolution is a novel sort of level set evolution that Li *et al*. [15] proposed in which level set model is presented by the following formulation in distance regularized level set evolution.

2. LEVEL SET FORMULATION WITH DISTANCE REGULARIZED

Considering the following equation:

$$\mathcal{E}(\emptyset) = \mu R_p(\emptyset) + \mathcal{E}_{ext}(\emptyset) \tag{1}$$

Where $\mu > 0$ is constant, $\varepsilon_{ext}(\emptyset)$ represent the external energy and $R_p(\emptyset)$ is the level set regularization term which was also called penalty term defined by:

$$R_p(\emptyset) \triangleq \int_\Omega p(|\nabla\emptyset|)dx \tag{2}$$

Here p represent a potential function $p: [0\ \infty] \rightarrow \Re$. To maintain such a profile of the level set function, the potential function $p(s)$ must have minimum points at $s = 0$ and $s = 1$, $p(s)$ is a double-well potential since it has two minimum points defined as:

$$p_2(\mathrm{s}) = \begin{cases} \frac{1}{(2\pi)^2}(1 - \cos(2\pi s)) \text{ if s} \leq 1 \\ \frac{1}{2}(\mathrm{s}-1)^2, \text{if s} \geq 1 \end{cases} \tag{3}$$

Where $d_p(s) = p_2'(s)/s$ satisfies $|d_p(s)| < 1$ and $\lim_{s\rightarrow 0} d_p(s) = \lim_{s\rightarrow\infty} d_p(s) = 1$. Here $p_2{}'(s)$ is the derivative of $p_2(s)$. Consequently $\left|\mu d_p(|\nabla\emptyset|\right| \leq \mu$, which confirms the diffusion rate's boundedness for the potential p_2. We can write (1) as:

$$\frac{\partial\mathcal{E}}{\partial\emptyset} = \mu\frac{\partial R_p}{\partial\emptyset} + \frac{\partial\mathcal{E}_{ext}}{\partial\emptyset} \tag{4}$$

Where $\frac{\partial\varepsilon_{ext}}{\partial\emptyset}$ is the external energy functional's Gâteaux derivatives and $\frac{\partial R_p}{\partial\emptyset}$ is the level set regularization. Using the following evolution equation:

$$\frac{\partial\emptyset}{\partial t} = -\frac{\partial\varepsilon}{\partial\emptyset} \tag{5}$$

The energy's gradient flow becomes:

$$\frac{\partial\emptyset}{\partial t} = -\mu\frac{\partial R_p}{\partial\emptyset} - \frac{\partial\varepsilon_{ext}}{\partial\emptyset} \tag{6}$$

Knowing that $\frac{\partial R_p}{\partial\emptyset} = -div(d_p(|\nabla\emptyset|)\nabla\emptyset)$ the (1) becomes:

$$\frac{\partial\emptyset}{\partial \mathrm{t}} = \mu div\big(d_p(|\nabla\emptyset|)\nabla\emptyset\big) - \frac{\partial\mathcal{E}_{ext}}{\partial\emptyset} \tag{7}$$

The level set evolution (7) is known as a distance regularized level set evolution, this formulation can be used in image segmentation application using edge-based information g. In this case a functional energy $\varepsilon(\emptyset)$ is defined by:

$$\mathcal{E}(\emptyset) = \mu R_p(\emptyset) + \lambda \mathcal{L}_g(\emptyset) + \alpha \mathcal{A}_g(\emptyset) \tag{8}$$

Where $\lambda > 0$, $\alpha \epsilon \mathcal{R}$ constants, the terms $\mathcal{L}_g(\emptyset)$ and $\mathcal{A}_g(\emptyset)$ are defined by: $\mathcal{L}_g(\emptyset) \triangleq \int_\Omega g\delta(\emptyset)|\nabla\emptyset|dx$ and $\mathcal{A}_g \triangleq \int_\Omega gH(-\emptyset)dx$. Where δ is the Dirac delta function and H represent the Heaviside function. The functional energy $\varepsilon(\emptyset)$can be minimized by solving the following gradient flow:

$$\frac{\partial\emptyset}{\partial t} = \mu div\big(d_p(|\nabla\emptyset|)\nabla\emptyset\big) + \lambda\delta(\emptyset) div\left(g\frac{\nabla\emptyset}{|\nabla\emptyset|}\right) + \alpha g\delta(\emptyset) \tag{9}$$

Model in (9) is an edge-based geometric active contour, which is an image segmentation application of the general distance regularized level set evolution (8). According to the theory presented above, the distance regularization effect eliminates the need for reinitialization and therefore avoids its induced numerical errors. The diffusion rate is transformed into a bounded constant by optimizing the penalty term's function, and adequate numerical precision was achieved. Unfortunately, this model could not escape the following inconvenients:
a) When using real medical images or noisy images, this model will produce blurred edge since it utilizes a Gaussian filter to decrease the noise.
b) This model cannot segment in a correct way because it must artificially determine the model's constant evolution speed's symbol based on the location of the initial curve.
c) The background boundaries and target boundaries are not distinguished by the edge indicator function g, however, in a single image, the target boundaries and background boundaries typically have completely different gradient directions.

To overcome these disadvantages, several methods are proposed for example paper [16] demonstrat, both theoretically and experimentally, that indirect regularization has some advantages over direct regularization, Yu *et al*. [17] suggest novel active contour model (R-DRLSE model) for image segmentation and Young *et al*. [18] develop a new approach to contour evolution. Liu and Xu [19] propose oriented distance regularized level evolution and Cai [20] propose a coupled model for image segmentation and restoration.

Messaouda *et al*. [21] present a novel level set method driven by new signed pressure force function (SPF) for image segmentation. In this paper a novel method is proposed to simultaneously solve a two-dimensional partial differential equations (PDE) system, make a compromise between image restorations and keep edges and correct segmentation. The first PDE of the system allows the restoration of the image by adopting regularized Perona and Malik equation filter that removes noise and preserves edge information in accordance with the detected contours in the second PDE, the second equation is based on level set model which uses the evolution of a curve propagating in a plane of its normal with a given speed.

This evolution is guided by a function that allows to stop the curve on the edges of objects to be detected in the image restored by the first equation [22]. This paper is organized as: after presenting the introduction in this section, the proposed method will be presented in section 3. Section 4 deals with simulation experiments that justify the paper contribution in applied field. Section 5 provides a conclusion for the achieved results.

3. METHOD

Usually, in all the active contour models, an edge detector is used to stop the evolving curve on the boundaries of the desired object. This is a positive and regular edge-function $g(|\nabla f|)$. Where $\lim_{t\to\infty} g(t) = 0$ and $g(|\nabla f|) = \frac{1}{1+|\nabla G_\sigma * f|^2}$ with $G_\sigma(x,y) = \sqrt{\sigma}\exp\left(-\frac{|x^2+y^2|}{4\sigma}\right)$. Where $G_\sigma \times f$ is the convolution of the image f with the Gaussian kernel (G,σ), which give a smoother version of the image. The edge-function $g(|\nabla f|)$ is strictly positive in homogeneous regions, and near zero on the edges. All these classical active contour models are based on this edge-function which depend to the gradient of the image to stop the curve evolution. But during the implementation of those methods that the discrete gradients are limited and then the stopping function $g(|\nabla f|)$ is never zero at the edges, and the curve may exceed the limits. In other words, if the image is heavily noisy, then the smoothing process has to be strong, which will smooth the edges too. To resolve this problem, a new approach is proposed to overcome the disadvantages of this model.

The aim of this approach is to unify the image restoration and segmentation to achieve those two tasks at the same time. Often with a Gaussian kernel (G,σ) the choice of the variance σ is difficult: if the smoothing is too large, the edges of the image is lost; if the smoothing is too low, the spread of the curve is determined by the noise before the contours are achieved. So, the results are not always satisfactory in this kind of filtering, which adversely affects the results of segmentation.

In order to estimate image f and reducing image noise while preserving edge details which facilitates a correct segmentation, a new method is proposed to jointly perform a restoration using an anisotropic smoothing based on Euler's equation as well as make the restoration results more continuous and smooth [23]. For this, a regularized method with contour preservation is used [24]. These contours are detected by the segmentation performed at the same time. In this case we can estimate the image f using the following PDE as:

$$H^*(Hf - y) + \lambda div(K\nabla f) = 0 \tag{10}$$

Where f and y denote vectors containing the true and the observed image respectively, H is the observation matrix and λ is a hyper-parameter, or regularization parameter and K allows the preservation of discontinuities. Euler's (10) is the PDE associated with the minimization of the criterion.

$$J(f) = \int |Hf - y|^2 + \lambda^2 \int \varphi(|\nabla f)| \tag{11}$$

φ is a regularizing function; in this case:

$$K = \frac{\varphi'(|\nabla f|)}{2|\nabla f|} \tag{12}$$

In equation (10) is similar to the anisotropic diffusion in [25], [26], in which $K = c(|\nabla f|)$ is the coefficient of heat transmission. For our application, K depends on the contours calculated by (1). We have then, $K = k(\emptyset)$ where the function k satisfies the following conditions: $k(\emptyset)$ is close to 0 near C (C is represented as a level set of a function $\emptyset$) and near 1 elsewhere.

The function k evolves at the same time that the algorithm converges. Initially, the contour determined by C is not well localized, k is then a blurred version of $\emptyset$ so $k(\emptyset)$ away from C and slowly decreases to 0 near C. Then, as the convergence of the algorithm advance, C tends toward the contours of objects and k tends to a Boolean function where $k(\emptyset) = 0$ on C (the contours) and $k(\emptyset) = 1$ on homogeneous areas of the image. We use then a continuous function that checks:

$$\begin{cases} k(\emptyset) = 1 \; if \emptyset \geq e \\ k(\emptyset) lineare \; 0 < \emptyset < e \\ k(0) = 1 - \frac{1}{e} \end{cases} \tag{13}$$

The e decreases towards 1 as and as the algorithm evolves. The end result is a Boolean function if $e = 1$. By coupling (9) with (10), the new system of two PDE is:

$$\begin{cases} \frac{\partial f}{\partial t} = H^*(y - Hf) + \lambda div(k(\emptyset)\nabla f) \; (a) \\ \frac{\partial \emptyset}{\partial t} = \mu div\left(d_p(|\nabla\emptyset|)\nabla\emptyset\right) + \lambda\delta(\emptyset) div\left(g\frac{\nabla\emptyset}{|\nabla\emptyset|}\right) + \alpha g\delta(\emptyset) \; (b) \end{cases} \tag{14}$$

With the boundary conditions defined previously and the edge stop function $g(|\nabla f) = \frac{1}{1+|\nabla f/\gamma|^2}$. Where γ is a parameter which sets a threshold on the gradient of the objects to be detected.

Proposed Algorithm
The proposed algorithm consists of solving the system of two PDE: – (14.a) processes the image f according to ϕ – (14.b) processes the image distances ϕ of c according to f Those two PDE are alternatevly resolved as: Initialization $f_0 = 0$; ϕ_0 = signed distances of C_0 Repeat Iterate (14.a) until convergence on f, with ϕ fixed Iterate (14.b) until convergence on ϕ, with f fixed Repeat until convergence on f and ϕ. End process

4. RESULTS AND DISCUSSION

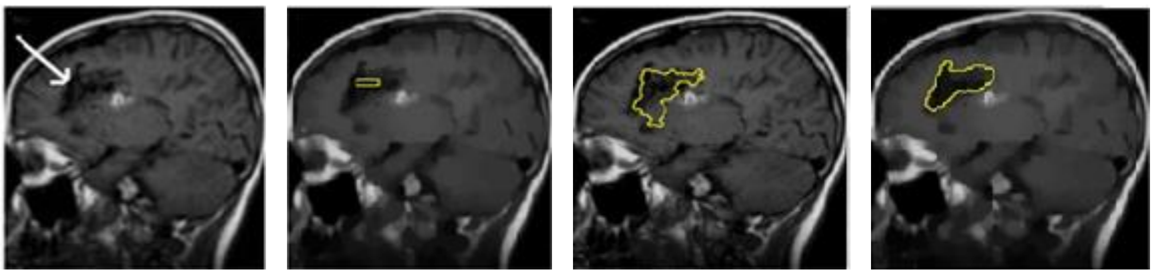
The spot's contour represents a very important characteristic in medical images. The extracted pathology's contour can help doctors to quantitate the spots, analyses the pathology, and conclude the diagnosis. In this experiment several medical images are used to check the robustness of the proposed approach. In the first experimental stage, the distance regularized level set evolution model is used for an application of the segmentation. In the second one, the proposed approach is applied considering the following parameters: μ, λ and α for this model, and time delay Δt for the implementation. Seting $\lambda = 5$, $\mu = 0.04$, $\Delta t = 10$ and α is variable depends on the image used.

Figure 1(a) to Figure 1(c) and Figure 2(a) to Figure 2(c) show employed medical images representing pathologies. Figure 1 represents a tumor of the liver, seen asa black spot. Image in Figure 2 represents a particular real medical image of GE system database, this image show the sagittal T1-weighted brain registered through an MRI scanner, contains black spots represent tumors. We see that level set model fail to settle on the correct boundary see Figure 1, and Figure 2, but the application of our proposed approach have been successful to detect the real edges see Figure 1 and Figure 2.

Taking at the results from level set model, we observe that this method can't give satisfactory results for such images. For further confirmation of the efficiency of our approach, we have tested our algorithm on two other images whose segmentation results are presented in Figure 3 including the three sub-figures Figure 3(a) to Figure 3(c). In Figure 4(a) to Figure 4(c) a heart's MRI image is used. From Figure 4(a) to Figure 4(c) and Table 1, it can be deduced that the proposed algorithm protects the edge information, needs less iteration times. Compared to other models, the proposed approach extracts the contour with greater accuracy.

(a) (b) (c)

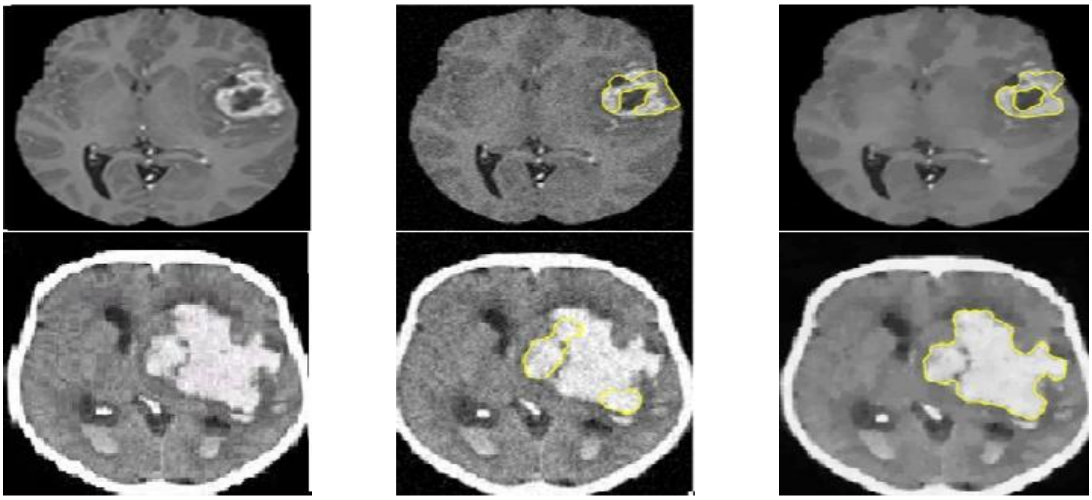
Figure 1. Results of segmentation using level set model and proposed approach: (a) the input image with initial contour; (b) image segmented with level set model; and (c) image segmented with proposed approach



(a) (b) (c) (d)

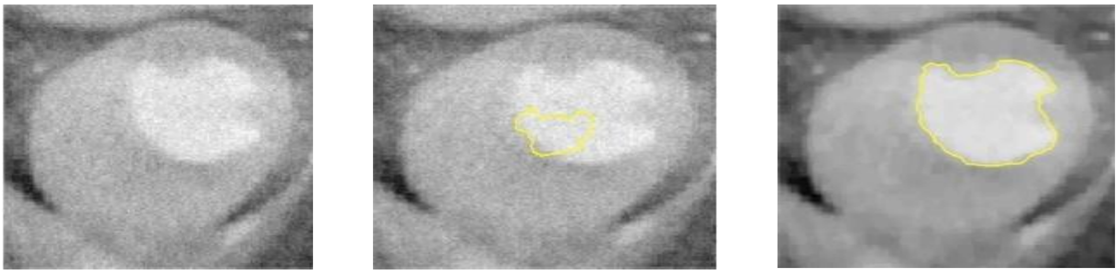
Figure 2. Results of segmentation using level set model and proposed approach: (a) the input image with pathology that we want to segment; (b) initial contour; (c) image segmented with level set; and (d) image segmented with proposed approach

Figure 5(a), Figure 5(b), Figure 5(c), and Figure 5(d) presents results of the segmentation of the hippocampus correspond to a subject with Alzheimer's in advanced stage. From Figure 6(a), Figure 6(b), Figure 6(c), and Figure 6(d), it can be conclude that the proposed algorithm has the ability to provide good image segmentation. which allows to reach a great contour accuracy for noisy medical images.



(a) (b) (c)

Figure 3. Results of segmentation using level set and proposed approach: (a) the input images; (b) image segmented with level set; and (c) image segmented with proposed approach

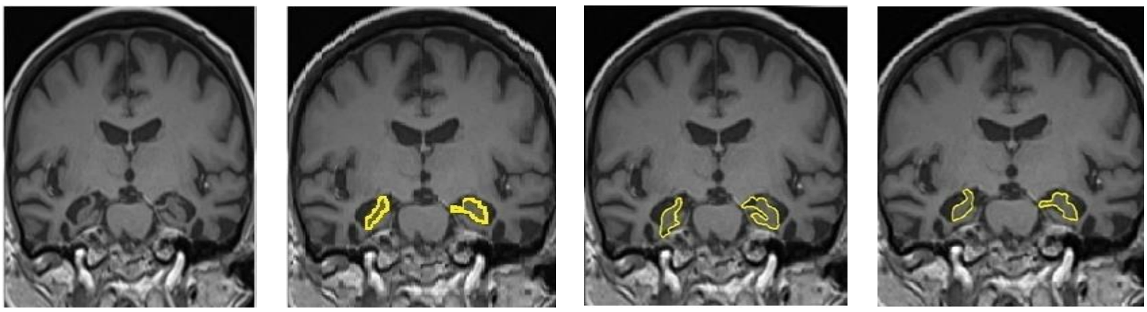


(a) (b) (c)

Figure 4. Results of segmentation: (a) the input image; (b) image segmented with level set; and (c) image segmented with proposed approach

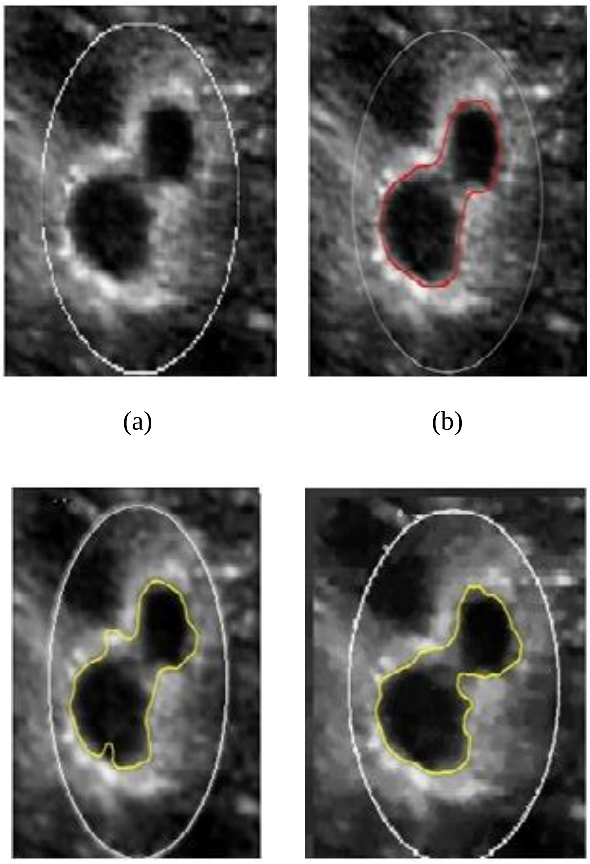
Table1. Data of experiments presented in Figure 4

Segmentation methods	Initial contour	Iteration	Cost	Time	Segmentation state
Level set	Internal	–	680	90 s	Not
Proposed approach	Internal	178	–	17 s	Achieved



(a) (b) (c) (d)

Figure 5. The results of the segmentation of the hippocampus correspond to a subject with Alzheimer's (advanced stage): (a) the input image; (b) manual image segmentation; (c) image segmented with lev set; and (d) image segmented with our proposed approach



(a) (b)

(c) (d)

Figure 6. Evolution results of the level with DRLSE method, the ODRLSE method and our approach: (a) initial image (an ultrasound image of liver tumor); (b) segmentation result DRLSE; (c) segmentation result ODRLSE method; and (d) segmentation result in proposed approach

5. CONCLUSION

In this paper, a level set method is used with distance regularized level set evolution applied on real medical images to detect pathologies. After several experiments, results still not satisfactory for the studied model because there is a trade-off between the noise elimination rate in image and good segmentation results. The proposed algorithm has the ability to provide good image segmentation. It shows great accuracy in extracting the contours of noisy medical images that allows reducing human intervention in the segmention process through applying the proposed approach to computer medical diagnosis to help improving image interpretation and investigation.

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