International Journal of Engineering Research and Technology.
ISSN 0974-3154 Volume 6, Number 1 (2013), pp. 61-73

http://www.irphouse.com

Region Based Active Contour Model For Intensity Non-Uniformity Correction For Image Segmentation

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Abstract

Intensity non-uniformities regularly occur in real-world images and may cause huge difficulties in image segmentation. For this problem, we propose a new model called region based active contour model. This model helps us to illustrate intensity information in local regions at controllable scale. A data fitting energy can be said as a contour and two fitting functions that locally approximate the image intensities on the two sides of the contour. This energy is then included into a variational level set formulation with a level set regularization term, from which a curve evolution equation is derived for energy minimization. Experimental results for synthetic & real images show desirable performances of our method.

Keywords: Intensity non-uniformity, Active contour models, Image Segmentation, Energy Minimization.

Introduction

Active contour model have been widely applied to image segmentation [1]-[3]. There are several enviable advantages of contour models over standard image segmentation methods such as Edge detection, Threshold and Region grow. First, active contour models attain sub-pixel accuracy of object boundaries [4]. Second, active contour models can be easily formulated under a righteous energy minimization structure. Third, they can provide smooth and closed contour as segmentation results. Presented Active contour models can be categorized into two major classes. They are (1) Edge based models [4], [7], [8], [3], [9], [10], (2) Region based models. [1], [11]-[14]. Edge based models use local edge information to catch the attention of the active contour towards the object boundaries. Region based models aim to discover each region of interest using a certain region descriptor to show the motion of the active contour. The region based active contour models [1], [11], [12], [15] tend to depend on intensity non-uniformity because in each of the segmented region there exist an intensity non-uniformity problem. For example, the popular Piecewise constant (PC) models are based on the statement that intensities are statistically homogenous in each region.

In fact, intensity non-uniformity often occurs in real-world images from modalities. For medical images, intensity non-uniformity is usually due to technical confines are art of work introduced by the object being imaged. In particular, the non-uniformities in magnetic resonance (MR) images arise from the non-uniform magnetic fields produced by radio frequency coils as well as from variations in object openness. Segmentation of such MR images usually requires intensity non-uniformity correction as preprocessing step [16]. Intensity non-uniformity can be addressed by more complicated models than PC models. Vese and Chan [14] and Tsai independently proposed two similar region-based models for more general images. Aiming at minimizing the Mumford–Shah functional, both models cast image segmentation as a problem of finding an optimal approximation of the original image by a piecewise smooth function. These models, widely known as piecewise smooth (PS) models, have exhibited certain capability of handling intensity non-uniformity. However, the PS models are computationally expensive and suffer from other difficulties. Recently, Michailovih [17] proposed an active contour model using the Bhattacharyya difference between the intensity distributions inside and outside a contour. Their model does not rely on the intensity homogeneity and, therefore, to some extent, overcome the limitation of PC models.

We propose a new region-based active contour model in a variational level set formulation. We first define a region- scalable fitting (RSF) energy functional in terms of a contour and two fitting functions that locally approximate the image intensities on the two sides of the contour. The best fitting functions are shown to be the averages of local intensities on the two sides of the contour. The region-scalability of the RSF energy is due to the kernel function with a scale parameter, which allows the use of intensity information in regions at a controllable scale, from small neighborhoods to the entire domain. This energy is then included into a variational level set formulation with a level set regularization term. In the resulting curve evolution that minimizes the associated energy functional, intensity information in local regions at a certain scale is used to compute the two fitting functions and, thus, guide the motion of the contour toward the object boundaries. As a result, the proposed model can be used to segment images with intensity non-uniformity. Due to the level set regularization term in the proposed level set formulation, the regularity of the level set function is fundamentally preserved to ensure accurate computation for the level set evolution and final results, and avoid expensive reinitialization procedures.

Our model originally termed as local binary fitting model. Recently, local intensity averages were also introduced to active contour models in the context of geodesic active contour model or piecewise smooth models [20]-[22]. These models exhibit certain capability of handling intensity non-uniformity. Local intensity averages are derived as minimizes of the proposed energy functional in a dissimilar variational formulation.

Active Contour Models

Let $\Omega \subset R^2$ be the image domain, and $I : \Omega \rightarrow R$ be a given gray level image. In Mumford and Shah formulated the image segmentation problem as follows: given an image I, find a contour C which segments the image into non overlapping regions. They proposed the following energy functional:

$$F^{MS}(u, C) = \int_{\Omega} (u - I)^2 dx + \mu \int_{\Omega \setminus C} |\nabla u|^2 dx + v|C| \tag{1}$$

Where $|C|$ is the length of the contour C. The minimization of Mumford–Shah functional results in an optimal contour C that segments the given image I, and an image u that approximates the original image I and is smooth within each of the connected components in the image domain Ω separated by the contour C. In practice, it is difficult to minimize the functional (1) due to the unknown contour C of lower dimension and the non convexity of the functional. Chan and Vese [1] proposed an active contour approach to the Mumford–Shah problem for a special case where the image in the functional (1) is a piecewise constant function. For an image $I(x, y)$ on the image domain **Ω**, they propose to minimize the following energy:

$$F^{CV}(C, c_1, c_2) = \lambda_1 \int_{outside(c)} |I(x) - c_1|^2 dx + \lambda_2 \int_{inside(C)} |I(x) - c_2|^2 dx + v|C| \tag{2}$$

Where outside(C) and (C) represent the regions outside and inside the contour C, respectively, and c_1 and c_2 are two constants that approximate the image intensity in outside(C) and inside(C). We call the first two terms in (2) the global fitting energy. This energy can be represented by a level set formulation, and then the energy minimization problem can be converted to solving a level set evolution equation [1]. The optimal constants c_1 and c_2 that minimize the above global fitting energy are the averages of the intensities in the entire regions outside(C) and inside(C), respectively. Such optimal constants and can be far away from the original image data, if the intensities within outside(C) or inside (C) are not homogeneous. Likewise, more general piecewise constant models in a multiphase level set framework [11], [14] are not applicable for such images either.

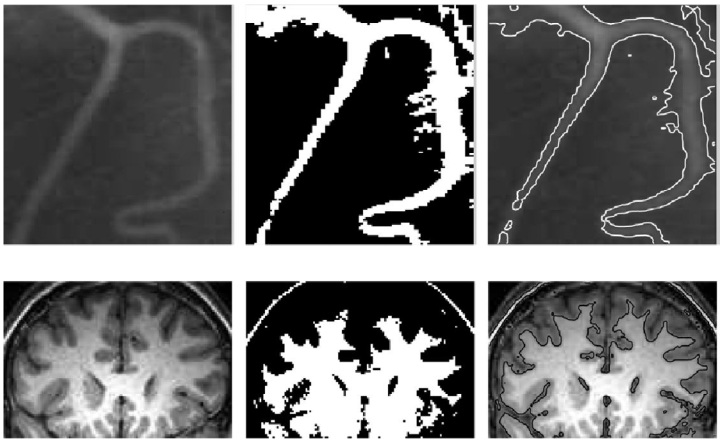

Fig.1. Error of thresholding and Chan–Vese model for images with intensity non-uniformity.
Column 1: Original images. Column 2: Thresholding results. Column 3: Results of Chan–Vese's PC model

The difficulties in segmenting images with intensity non-uniformity can be seen from the following examples. The vessel image and a brain MR image in the first column in Fig. 1 are typical examples of images with intensity non-uniformity. For such images, simple thresholding cannot segment them correctly. In fact, no matter what threshold value is selected, some part of the background foreground is incorrectly identified as the foreground/background, as shown in the second column. The third column of Fig.1 shows similar erroneous results obtained by applying Chan and Vese's PC model. These examples show the inability of the PC model and simple thresholding in segmenting images with intensity non-uniformity. The difficulties in segmenting images with intensity non-uniformity can be seen from the following examples. The vessel image and a brain MR image in the first column in Fig. 1 are typical examples of images with intensity non-uniformity. For such images, simple thresholding cannot segment them correctly. In fact, no matter what threshold value is selected, some part of the background/foreground is incorrectly identified as the foreground/background, as shown in the second column. The third column of Fig.1 shows similar erroneous results obtained by applying Chan and Vese's PC model [1]. These examples show the inability of the PC model and simple thresholding in segmenting images with intensity non-uniformity. The PS models in [14] and [13] overcome the limitation of PC models in segmenting images with intensity non-uniformity. In [14] Vese and Chan introduced energy functional on a level set function and two smooth functions u^+ and u^- that are defined on the regions outside and inside the zero level contour of a level set function □, respectively.

The energy functional has a data fitting term, which describes the approximation of the image by u^+ and u^- in their corresponding sub regions, and a smoothing term that forces u^+ and u^- to be smooth. The minimization of the energy functional in the PS model consists of the following three computational tasks. The first one is to solve the PDE of the main function by a sequence of iterations. Second, at every certain number of iterations for, the fitting functions u^+ and u^- have to be updated by solving two elliptic PDEs. Third, the functions u^+ and u^-, which are defined on different regions, have to be extended to the entire image domain. In addition, periodic reinitialization is typically necessary to repair the level set function degraded by the evolution. Obviously, the involved computation in PS model is expensive, which limits its applications in practice.

Region-Scalable Fitting Model

A. Region-scalable fitting energy

In this section, we propose a region-based model using intensity information in local regions at a controllable scale. We first introduce a nonnegative kernel function $K:\Re^n \to [0,+\infty)$ with the following properties:

1) $K(-u)=K(u);$
2) $K(u)\geq K(u), if\,|u|<|v|, and \lim_{|u|\to\infty} K(u)=0;$
3) $\int K(x)dx=1.$

We call property 2) a localization property of the kernel K .The kernel function and its localization property play a key role the proposed method. Consider a given vector valued image, $I:\Omega \to R^d$ where $I:\Omega \to R^d$ is the image domain, and $d \geq 1$ is the dimension of the vector I(x). In particular, d=1for gray level images, while d=3 for color images. Let C be a closed contour in the image domain Ω, which separates Ω into two regions: Ω_1=outside(C) and Ω_2=inside(C). For a given point $X \in \Omega$, we define the following local intensity fitting energy:

$$\varepsilon_x^{Fit}(C, f_1(x), f_2(x)) = \sum_{i=1}^{2} \lambda_i \int_{\Omega_i} K(x-y)|I(y)-f_i(x)|^2 dy \tag{3}$$

where λ_1 and λ_2 are positive constants, and $f_1(x)$ and f_2 (x) are two values that approximate image intensities in Ω_1 and Ω_2, respectively. The intensities I(y) that are effectively involved in the above fitting energy are in a local region centered at the point X, whose size can be controlled by the kernel function K, as explained below. Therefore, we call the local intensity fitting energy in (3) a region-scalable fitting (RSF) energy of a contour C at a point X. The choice of the kernel function k is flexible, as long as it satisfies the above three basic properties. In this paper, it is chosen as a Gaussian kernel

$$K_\sigma(u) = \frac{1}{(2\pi)^{n/2\sigma^n}} e^{-|u|^2/2\sigma^2} \tag{4}$$

with a scale parameter $\sigma > 0$. It is necessary to elaborate on the meaning of the fitting energy ε_x^{Fit} defined by (3) in the following. First, ε_x^{Fit} is a weighted mean square error of the approximation of the image intensities outside and inside the contour C by the fitting values $f_1(x)$ and $f_2(x)$, respectively, with K(x-y) as the weight assigned to each intensity I(y) at y . Second, due to the localization property of the kernel function, the contribution of the intensity I(y) to the fitting energy ε_x^{Fit} decreases and approaches to zero as the point y goes away from the center point x. Therefore, the energy is dominated by the intensities I(y) of the points y in a neighborhood of x. In particular, the Gaussian kernel $K_\sigma(x-y)$ decreases drastically to zero as y goes away from. Roughly speaking, the Gaussian kernel $K_\sigma(x-y)$ is effectively zero when $|x-y|>3\sigma$. Therefore, only the intensities in the neighborhood $\{y:|x-y|\le 3\sigma\}$ are dominant in the energy ε_x^{Fit} .In this sense, we say that the fitting energy ε_x^{Fit} is localized around the point x.

The fitting energy in (3) is region-scalable in the following sense. The fitting values $f_1(x)$ and $f_2(x)$ approximate the image intensities in a region centered at the point x, whose size can be controlled by the scale parameters σ . The fitting energy (3) with a small σ only involves the intensities within a small neighborhood of the point x, while the fitting energy with a large σ involves the image intensities in a large region centered at x. Note that, in our preliminary work [19], the energy (3) was termed as a local fitting energy, as opposed to the global fitting energy (2) in Chan and Vese's PC model [1]. However, it is more appropriate to call the energy (3) a region-scalable fitting energy, since the intensities I(y) for the fitting energy (3) are not restricted to a small local region. In fact, the intensities for the fitting energy (3) can be in a region of any size: from a small neighborhood to the entire image domain. This region-scalability is a unique and desirable feature of the proposed method.

$$\int \varepsilon_x^{Fit}(C,\ f_1(x),\ f_2(x))\,dx$$

Given a center point x, the fitting energy ε_x^{Fit} can be minimized when the contour C is exactly on the object boundary and the fitting values f_1 and f_2 optimally approximate the local image intensities on the two sides of C. To obtain the entire object boundary, we must find a contour C that minimizes the energy ε_x^{Fit} for all in the image domain **Ω**. This can be achieved by minimizing the integral of ε_x^{Fit} over all the center points x in the image domain **Ω**, namely,
In addition, it is necessary to smooth the contour C by penalizing its length |C|, as in most of active contour models. Therefore, we define the following energy functional:

$$\varepsilon(C,\ f_1(x),\ f_2(x)) = \int \varepsilon_x^{Fit}(C,\ f_1(x),\ f_2(x))\,dx + v|C|. \tag{5}$$

This energy functional is defined for a contour C. To handle topological changes, we will convert it to a level set formulation in the next subsection.

B. Level Set Formulation

In level set methods [23], a contour $C \subset \Omega$ is represented by the zero level set of a Lipschitz function $\phi : \Omega \to \Re$, which is called a level set function. In this paper, we let the level set function ϕ take positive and negative values outside and inside the contour C, respectively. Let H be the Heaviside function, then the energy functional $\varepsilon_x^{fit}(C, f_1(x), f_2(x))$ can be expressed as

$$\varepsilon_x^{Fit}(\phi, f_1(x), f_2(x)) = \sum_{i=1}^{2} \lambda_i \int K_\sigma(x-y)\left|I(y) - f_i(x)\right|^2 M_i(\phi(y))dy \tag{6}$$

Where $M_1(\phi) = H(\phi) and M_2(\phi) = 1 - H(\phi)$.thus, the energy ε in (5) can be written as (7), shown at the bottom of the next page, where the last term $\int |\nabla H(\phi(x))| dx$ computes the length of the zero level contour of ϕ. Note that this length term has been commonly used in variational level set methods for the regularization of the zero level contour [1], [14]. The length of the zero level contour can be equivalently expressed as the integral $\int \delta(\phi)|\nabla\phi| dx$ with the Dirac delta function , which has often been used in variational level set methods [5], [8].

$$\varepsilon(\phi, f_1, f_2) = \sum_{i=1}^{2} \lambda_i \int \left(\int K_\sigma(x-y)\left|I(y) - f_i(x)\right|^2 M_i(\phi(y))dy \right)dx + v\int |\nabla H(\phi(x))| dx \tag{7}$$

In practice, the Heaviside function in the above energy functional is approximated by a smooth function H_e defined by

$$H_\varepsilon(x) = \frac{1}{2}\left[1 + \frac{2}{\pi}\arctan\left(\frac{x}{\in}\right)\right] \tag{8}$$

The derivative of $H_\in$ is

$$\delta_\in(x) = H'_\in(x) = \frac{1}{\pi}\frac{\in}{\in^2 + x^2}. \tag{9}$$

By replacing H in (7) with $H_\in$, the energy functional ε in (7) is then approximated by

$$\varepsilon_\in(\phi, f_1, f_2) = \sum_{i=1}^{2} \lambda_i \int \left(\int K_\sigma(x-y)\left|I(y) - f_i(x)\right|^2 M_i^\in(\phi(y))dy \right)dx + v\int |\nabla H_\in(\phi(x))| dx \tag{10}$$

where $M_1(\phi) = H(\phi) and M_2(\phi) = 1 - H(\phi)$.

To preserve the regularity of the level set function, which is necessary for accurate computation and stable level set evolution, we introduce a level set regularization ϕ

term in our variational level set formulation. As proposed in [8], we define the level set regularization term as

$$p(\phi) = \int \frac{1}{2}\left(\left|\nabla \phi(x)\right| - 1\right)^2 dx \tag{11}$$

which characterizes the deviation of the function from a signed distance function. Therefore, we propose to minimize the energy functional

$$f(\phi, f_1, f_2) = \varepsilon_{\in}(\phi, f_1, f_2) + \mu p(\phi) \tag{12}$$

Where μ is a positive constant .To minimize this energy functional, its gradient flow is used as the level set evolution equation in the proposed method.

C. Energy Minimization

We use the standard gradient descent (or steepest descent) method to minimize the energy functional (12). For a fixed level set function ϕ, we minimize the functional $F(\phi, f_1, f_2)$ in (12) with respect to the functions $f_1(x)$ and $f_2(x)$. By calculus of variations, it can be shown that the functions $f_1(x)$ and $f_2(x)$ that minimize $F(\phi, f_1, f_2)$ satisfy the following Euler–Lagrange equations:

$$\int K_\sigma(x - y) M_i(\phi(y))(I(y) - f_i(x))dy = 0, i = 1,2. \tag{13}$$

From (13), we obtain

$$f_i(x) = \frac{K_\sigma(X) * \left[M_i^{\in}(\phi(x))\, I(x)\right]}{K_\sigma(X) * M_i^{\in}(\phi(X))}, i = 1,2 \tag{14}$$

which minimize the energy functional $F(\phi, f_1, f_2)$ for a fixed ϕ. The functions $f_1(x)$ and $f_2(x)$ given by (14) are weighted averages of the intensities in a neighborhood of x , whose size is proportional to the scale parameter σ . Note that the denominators in (14) are always is positive, due to the fact that $M_1^{\varepsilon} = H_{\in}(\phi) > 0$ and $M_2^{\in}(\phi) = 1 - H_{\in}(\phi) > 0$ by the definition $H_{\in}$ of in (8). Keeping and fixed, we minimize the energy functional with respect to using the standard gradient descent method by solving the gradient flow equation as follows:

$$\frac{\partial \phi}{\partial t} = -\delta_{\in}(\phi)(\lambda_1 e_1 - \lambda_2 e_2) + v\delta_{\in}(\phi) div\left(\frac{\nabla \phi}{|\nabla \phi|}\right) + \mu\left(\nabla^2 \phi - div\left(\frac{\nabla \phi}{|\nabla \phi|}\right)\right) \tag{15}$$

where is the smoothed Dirac delta function given by (9), and are the functions

$$e_i(X) = \int K_\sigma(y - x)\left|I(x) - f_{i(y)}\right|^2 dy, i = 1,2 \tag{16}$$

where f_1 and f_2 are given by (14). The above (15) is the level set evolution equation to be solved in the proposed method. The term $-\delta_{\in}(\phi)(\lambda_1 e_1 - \lambda_2 e_2)$ is derived from the data fitting energy, and, therefore, is referred to as the data fitting term. This term plays a key role in the proposed model, since it is responsible for driving the active contour toward object boundaries. The second term

$v\delta_{\epsilon}(\phi)div\left(\nabla\phi/|\nabla\phi|\right)$ has a length shortening or smoothing effect on the zero level contour, which is necessary to maintain the regularity of the contour. This term is called the area length term. The third term $\mu(\nabla^2\phi - div(\nabla\phi/|\nabla\phi|))$ is called a level set regularization term, since it serves to maintain the regularity of the level set function.

Experimental Results

The proposed method has been tested with real images from different modalities. Unless otherwise specified we use relatively small scale parameter for the experiments in this section. In general, our method with a smaller scale can produce more accurate location of the object boundaries, while it is more independent of the location of the initial contour when a larger is used.

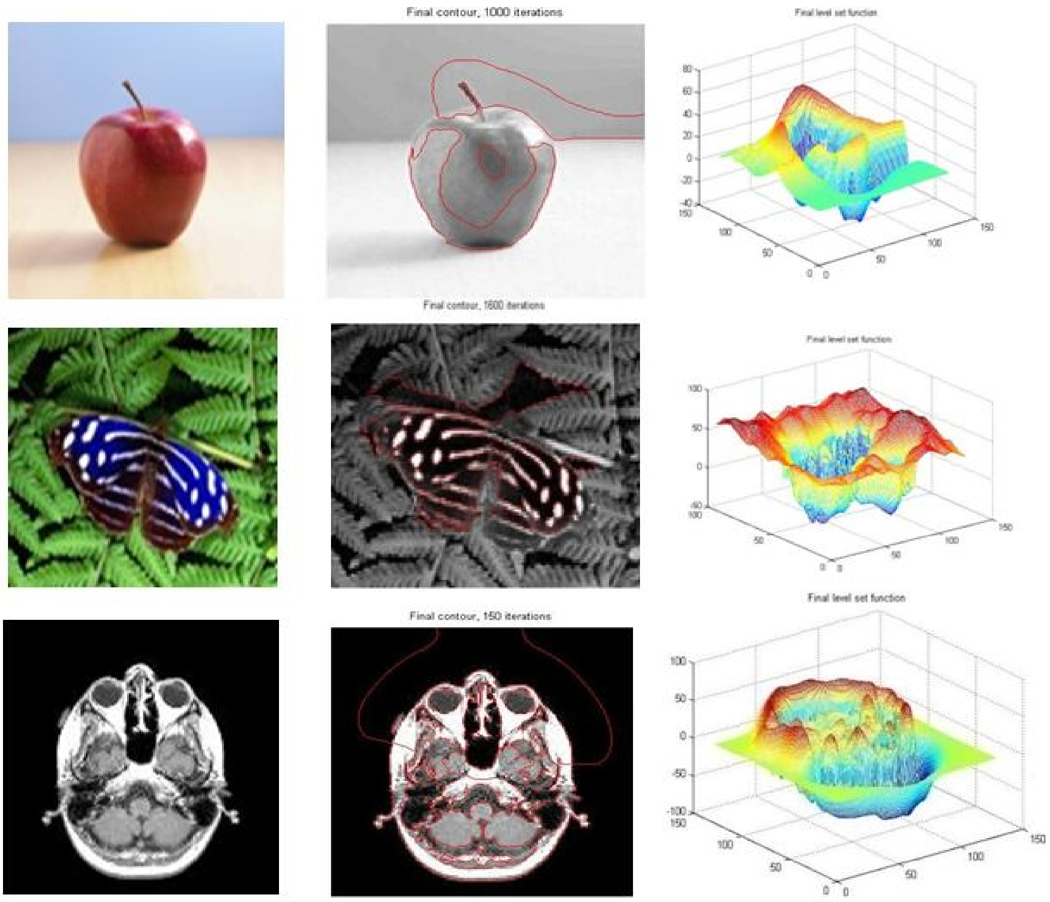

Fig.2. The left most image is the original image, the middle image is the segmented result & the right most picture is the final level set function

Here the left most image is the original image, Contains original information. The middle image is the segmented image which is obtained by using 150-1000 iterations. The segmented results shows objects with the Red outline as shown in the above; the right most images gives us the information about the corresponding image which works on the Gaussian function and called the image as final level set function. The results shown above are obtained after the non-uniformity correction. But if we do not consider the non-uniformity, the results may contain some regions with possible wrong boundaries. The results shown above can be compared to that of Chan Vese shown in fig. 1. The solution of N partial differential equations requires a considerable amount of time and hence the time consuming as well as complex.

Conclusions

In this paper we have presented a new region-based active contour model that lies upon intensity information in local region. The proposed technique is able to segment images with intensity non-uniformity, and has desirable performance for images with weak object boundaries. With the level set regularization term in the proposed level set formulation, the regularity of the level set function is intrinsically preserved to ensure accurate computation and avoid expensive reinitialization procedures. The present method overcomes the disadvantage of instability of contour initialization. Experimental results have demonstrated the advantages of our method over several well-known methods for image segmentation.

Acknowledgements

At the outset we express our gratitude to Dr. P Gopal Reddy sir, Director, PDCE, Sullurpet, Dr. A Siva Sankar sir, Principal, PDCE, Sullurpet, and the faculty members Y Ravi Sankaraiah sir, MS Abdullah sir, B Chandra Sekhar sir, V Kiran Kumar sir, S Sri Harshith sir, M Chiranjeevi sir, M Balaji Kumar sir, P Srinivasulu sir, M Gangadhar sir, E Sasikala madam, K Bharathi madam, G Sumalatha madam and D Baba Prasad sir who have guided us in completing this work with their esteemed cooperation and valuable guidance, and who has given our work a shape and success.

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