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Creative Economy, the Smart Factory, and ICT: Applying an Image Restoration Method on Blurred Image Using Inverse Diffusion Equation with Parameter in the Smart Factory

In Jung Lee* · Chang Jin Kee**

*Computer Engineering Part, Hoseo University
**Computer Science Department, Namseoul University

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Ⅰ. Introduction

Creative Economy, one of the top three core strategies for Economy Revival by the Park Guen-hye government, aims to upgrade Korea's manufacturing industries through the convergence of IT and software engineering [1]. This convergence is heading for shifting the manufacturing paradigm from traditional Mass Production to Mass Customization for the 21stcentury. This is whatt he Germany's Industry4.0[2] project aims to.

The Smart factory is the heart of the Industry 4.0 project and has already been adapted to German companies, such as Siemens and BMW. Its primary characteristics are adaptability, resource efficiency and ergonomics as well as the integration of customers and business partners in business and value processes. It is based on cyber-physical systems and IoT(Internet of Things) technologies [3].

RFID (Radio Frequency Identification) is the one of essential technologies enabling these technologies, but its creditability tends to fall down when passive RFID tags are under strong radio noises and fast moving objects/readers. Under these environments, passive RFID tags may cause the unreliability of object detection because of object occlusion phenomenon. In order to cope with object occlusion phenomenon, cameras are integrated into passive RFID tag systems. The object detection by cameras are, however, still needs to solve blurring problem. This paper introduces a technology to recover blurred images.

Monitoring systems have been developed by CCTV for the Smart Factory. The CCTV systems are very effective in monitoring and supporting incident management.

If an operator wants to observe an omnidirectional view in his office at the same time, he needs four CCTV cameras or a convex-mirror camera [7] or a fisheye lens camera. When he wants to get some information, he needs to install a detection zone in CCTV images. Installing is not easy because of machine error. Since after pan-tilt operation a new detect zone is needed, we must use an improved CCTV with a fisheye lens or convex mirror which has a wider view than an ordinary CCTV system. There are some problems however such as a distortion across the hemispherical field in the fisheye view as shown in (Fig.1).

Also a transformation algorithm is necessary to transform a fisheye image into a de-warped image.

When a fisheye image is spread out into a de-warped image, some blurring occurs,

Fig.1 Fisheye view

because a small size fisheye view is spread out to make a larger size de-warped image as shown as (Fig.2).

Fig.2 Blurring in de-warped image

In this paper, a de-blurring method is introduced using nonlinear diffusion equation and deformation method. Some experimental results and the performance of detection systems from de-blurred images rather than blurred images are shown.

Ⅱ. Nonlinear Diffusion Equation and Deformation

A mathematical formulation of de-warping is as follows. Let a point p(x,y,z) be in the fisheye image and a corresponding point q(a,b) be in flat image as shown in (Fig.3).

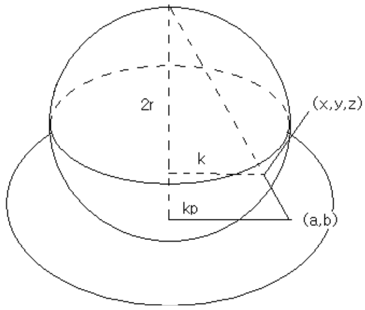


Fig.3 A matching from one point (x,y,z) on a sphere to the point (a,b) on disc.

Then we can transform p(x,y,z) to q(a,b) through the equation 1,2,

$$a = \frac{2xr}{2r - z} \tag{1}$$

$$b = \frac{2yr}{2r - z} \tag{2}$$

where r is the radius of fish-eye image. So the de-warped image is shown by this transform in (Fig.4).

In this section, we introduce a discontinuous force function which has discontinuous right-hand side [8] in equation 3,

$$\frac{\partial u_n}{\partial t} = \frac{1}{m_n}(F(u_{n+1} - u_n) - F(u_n - u_{n-1}))$$
$$n = 1, 2, 3, \ldots N \tag{3}$$

Where u_n is a discrete signal and F is a force function.

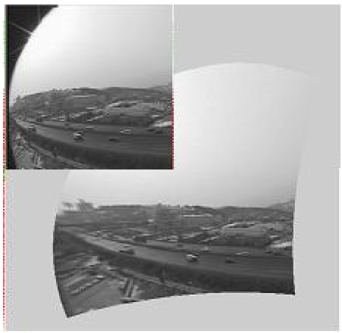


Fig.4 A transformed image from a fish-eye image applying equation 1,2.

These equations have received much attention in control theory because of the wide usage of relay switches in automatic control systems. More recently, the deliberate introduction of discontinuities has been used in control applications to drive the state vector onto lower-dimensional surfaces in the state space. As we will see, this objective of driving a trajectory onto a lower-dimensional surface also has value in image analysis and particularly in image segmentation. Segmenting a signal or an image, represented as a high-dimensional vector, is evolved, so that it is driven onto a comparatively low -dimensional subspace. This subspace corresponds to a segmentation of the signal or image domain into a small number of regions. The type of force function of interest to us here is illustrated in (Fig.5).

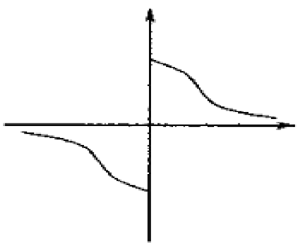


Fig.5 Force function

More precisely, we wish to consider force functions that satisfy the following properties such as

$$F'(v) \le 0 \text{ for } v \ne 0$$
$$F(0^+) > 0$$
$$F(v_1) = F(v_2) \text{ if and only if } v_1 = v_2 \quad (4)$$

Because of the discontinuity at the origin of the force function in Fig.6 however, there is a question of how one defines solutions of equation 4 for such a force function. If equation 4 evolves toward a point of discontinuity of its RHS, the value of the RHS of equation 4 apparently depends on the direction from which this point is approached, making further evolution non-unique. We therefore need a special definition of how the trajectory of our evolution proceeds at these discontinuity points. For this definition to be useful, the resulting evolution must satisfy well-posed properties, that is the existence and uniqueness of solutions, as well as stability of solutions with respect to the initial data. Viewed as a segmentation algorithm, our evolution can be summarized as follows:

1) It starts with the trivial initial segmentation, that is, each sample is a distinct region.

2) It evolves equation 5, until the values in two or more neighboring regions become equal.

$$\frac{\partial u_{n_i}}{\partial t} = \frac{1}{m_{n_i}}\left(F(u_{n_i+1} - u_{n_i}) - F(u_{n_i} - u_{n_i-1})\right)$$
$$u_{n_i} = u_{n_i+1} = \dots = u_{n_i+m_{n_i}-1} \quad (5)$$

where $i = 1,2,3,\dots,p$

$$1 = n_1 < n_2 < \dots < n_{p-1} < n_p < N$$
$$n_{i+1} = n_i + m_{n_i}$$

3) It merges the neighboring regions whose values are equal.

4) Go to step 2.

After applying this algorithm to a 256*256 gray image, we obtained a following image as shown in (Fig.6).

Fig.6 The result image after using equation 6.

Result is good from the not blurred image Lena, Result from the blurred image however is no good. We could not find the segmented area which is an important region for processing de-blurring. Beside, we must have small iteration number due to fastness. Under the same stability as shown in equation 5, we unavoidably lead out a parameter α such that

$$\frac{\partial u_{n_i}}{\partial t} = \frac{1}{m_{n_i}}(F(u_{n_i+1} - u_{n_i}) - \alpha F(u_{n_i} - u_{n_i-1}))$$

$$u_{n_i} = u_{n_i+1} = \ldots = u_{n_i+m_{n_i}-1} \qquad (6)$$

where $i = 1,2,3,\ldots,p$

$$1 = n_1 < n_2 < \ldots < n_{p-1} < n_p < N$$

$$n_{i+1} = n_i + m_{n_i}$$

Applying this algorithm again with equation 6 to a blurred image, resulted in as image as shown in (Fig.7).

Fig.7 The result image after using equation 6.

In this segmented area, the deformation method is used to get a de-blurred image [6]. The deformation equation is defined by equation 7, let a surface be Ω,

$$\frac{\partial \Omega}{\partial t} = \alpha(s,t) + \beta(s,t)N$$

$$\Omega(s,0) = \Omega_0(s) \qquad (7)$$

Where T is a tangent and N is a normal vector, α and ß are arbitrary function. From this equation 7, a curvature deformation equation is defined. Let a function of surface be

$$z = \phi(x,y,z)$$

$$\frac{\partial \Omega}{\partial t} = kN$$

$$\Omega(s,0) = \Omega_0(s) \qquad (8)$$

Where

$$k = \frac{(\phi_{xx}\phi_y^2 - 2\phi_{xy}\phi_x\phi_y + \phi_{yy}\phi_x^2)}{(\phi_x^2 + \phi_y^2)^{\frac{2}{3}}}$$

Applying equation 8 at a segmented area, a de-blurred image is obtained as shown in (Fig.8).

Fig.8 The de-blurred image is obtained at right from a blurred image at left.

Fig. 9 The blurred image and its de-blurred image are in the CCTV images.

When the proposed methods are applied to a real highway CCTV image, the de-blurred CCTV image is obtained at right from a de-warped fish-eye image at left as shown in (Fig.9).

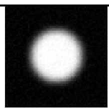
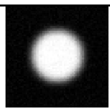
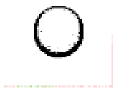
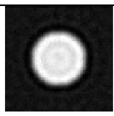
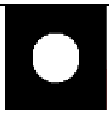
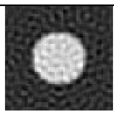
Method	Proposed method	Landweber method
A blurred & noised image		
Computing results intermediate	 Applying equation 4th iteration with $\alpha=1.7$	 32th iterations
The last results	 After deformation	 64th iterations
MSE (L^2-error)	7.8%/10th iterations	19%/110th iterations
Computing time	0.02 seconds	48 seconds

Fig.10 The Images or values comparing proposed method with Landweber method.

For evaluating de-blurring effectiveness and fastness, as stated already, we need a fast algorithm for a CCTV system. We shall compare this result with the results applying Landweber method [7] in (Fig.10) by (mean squared errors). Due to fastness computing time for each is compared.

Ⅲ. Performance Improvement of Moving Vehicle Detection System

A fish-eye image is transformed into a de-warped image in order to collect information. Image distortion is raised in transform process, problems are found during the finding vehicles. Therefore, as in section II, de-blurring is applied to a de-warped image in order to improve recognition performance. Actually, a vehicle is being tracked by using difference image and binary image as shown in (Fig.11). In order to get some information from the binary difference image, the area of a rectangle is determined for a moving vehicle as in (Fig.12). Equation 9 for this rectangle is used by performing find four line-segments along ① or ②.

Fig.11 The detection zone for tracking vehicle

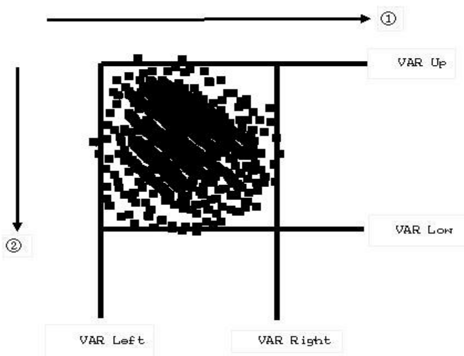


Fig.12 The area rectangle of moving vehicle

A binary function is defined:

$OccFlaggs : R \rightarrow 0.1$

by

$$OccFlaggs(x) = \begin{cases} 1 & \text{if } x > r \\ 0 & otherwise \end{cases} \quad (9)$$

Where $x = \frac{1}{N}\sum_{i=0}^{N-1} P_{i,j}$ along ② and $x = \frac{1}{N}\sum_{j=0}^{N-1} P_{i,j}$ along ①, $P_{i,j}$ is 0 or 1 and λ is a determining factor. The factor λ is obtained by experiments and is about 20%. If the image is blurred however, the correct line will be missed. The detection zone is misread due to getting low value x compared to λ at every line along ① and ② (Fig.13).

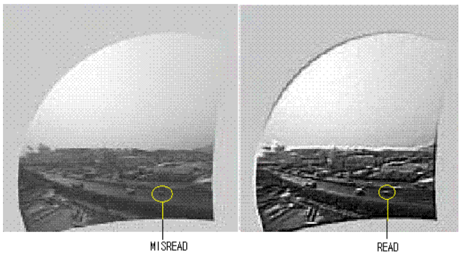
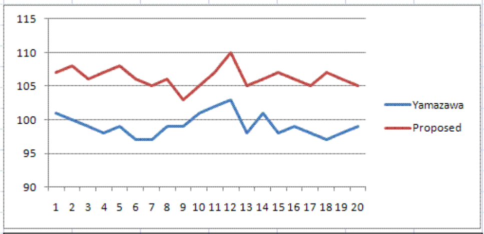


Fig.13 The case of misread the detection zone.

Because of this reason, the obtained information from the blurred images is less accurate than from the de-blurred images. The accuracy is also low in terms of speed. Some experimental results are shown in aspect of vehicle speed. This vehicle speed is compared the proposed method with Yamazawa method [8]. Those experimental processes are played 20th from the same saved video file images. The performance of proposed method is 5% better than Yamazawa method as shown in (Fig.14). In spite of de-blurring, the performance of proposed method is not improved more than the performance obtained from the ordinary camera images. In this experimental process, every speed datum is chosen provabilistic in the interval 2 distance from the mean. It is evidence that this experimental system is stable.



	proposed	Yamazawa
mean	106.25	99.15
stdev	1.48	1.69

Fig.14 The vehicle speed is compared the proposed method with Yamazawa method.

Ⅳ. Conclusions

A fish-eye lens or convex mirror camera is necessary for getting wide area images in the Smart Factory. There are some problems, due to these problems, the system speed is decreased and image distortion is raised. In this paper, two methods of de-blurring for overcoming distortion are proposed. One is image segmentation by nonlinear diffusion equation. The other is deformation for segmented areas. The result of applying de-blurring methods shows that the proposed method has 11% of increased MSE more than Landweber method. The performance of proposed method is 5% better than Yamazawa method.

This paper shows how the goal of Creative Economy - upgrading Korea's manufacturing industries through the convergence of IT and software engineering could be implemented in the Smart Factory environment. Solution to the occlusion problem of passive RFID tags is suggested. It could be embedded in passive RFID tag systems along with cameras as a software.

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이인정(In Jung Lee)

1990년: 중앙대학교 대학원 수학과(이학박사)
2002년: 아주대학교 대학원 전자공학과(공학박사)
1992년~현재: 호서대학교 교수
※관심분야: 영상처리, 알고리즘

기창진(Chang Jin Kee)

1995년: Dept. of Electrical and Computer Engineering, University of South Carolina(공학박사)
2002년: VP & Co-founder, Omegagen, MD, USA.
2013년~현재: 남서울대학교 컴퓨터학과 교수
※관심분야: SSPL(Software and Systems Product-line Engineering), MOOC Architecture, Software Architecture