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Dynamic Image Cognition and Its Application to Visualized Information

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Abstract: This paper deals with a method of dynamic image cognition and its applications. Our dynamic image cognition has two distinct features. One is that the dynamic image is handled as its eigen pattern. The other is that the cognition is carried out by solving the ill-posed linear system of equations comprising the eigen patterns as a database. The eigen pattern consists of histograms in terms of intensity, tones and primal color components of dynamic image. This combination of color components yields a numerical data set, which is hard to be changed by the differences in spatial position of target as well as resolution of the image. Practical cognitions of objects moving and visualized magnetodynamic fields reveal that the dynamic image cognition approach gives more reliable solution than that of static image cognition.

Keywords: Dynamic Image Cognition, Eigen Pattern, Visualized Information, Ill-posed Liner System of Equation

1. Introduction

Many technologies employing digital computers are developed to realize the human brain functions, e.g. artificial intelligent (AI) and artificial neural network (ANN). Even if we limit only the function of human eyes, any computer image processing technologies could not realize that function exactly. This is because the human brain informed by seeing, hearing, etc, makes it possible to cognize a target object exactly. Furthermore, it may be considered that the human brain extracts the essential characteristics of target object by seeing and hearing. The extraction of such essential characteristics from the target object is of paramount importance in computer science, but it has not been accomplished yet.

In this paper, target objects of the image cognition are defined as cognizable information by the human eyes, and they are called "visualized information" (Sato et al., 2001). The picture or image obtained by camera is considered as visualized information. Infrared and electron microscope are also capable of visualizing something that is directly invisible for the human eyes. Even if the information is invisible, the signals obtained make it possible for the human eyes to cognize the information by specific ways.

In case of the human brain, the information is recognized by seeing, hearing and so on. Information by seeing and hearing is classified into two kinds of audiovisual information. One is encoded audiovisual information such as an encoded character and a language by a specific rule. The other is non-encoded audiovisual information. The visualized information such as a visualized image is one of the non-encoded audiovisual information. Human being senses some characteristics from the visualized information, however, it is important for computer sciences to extract the essential characteristics from the visualized information in order to realize the human brain (Wakabayashi et al., 1999).

A digital image on two-dimensional plane is composed of a set of the pixels, and is represented by geometrical arrangement of the pixels. Thereby, the digital images depend on their resolution and spatial position on the screen. The key idea of characteristic extraction is to introduce the eigen pattern, which represents the essential characteristics of digital images independent of their resolution and spatial position on the screen (Sato et al., 2002). As a result, our approaches have succeeded in cognizing images beyond the human eyes.

2. Eigen Pattern of Visualized Information

2.1 Eigen Pattern Elements

The eigen pattern is composed of eigen vectors of three components- intensity, tone and color component. The elements of intensity eigen vector are given by the sum of red, green and blue components of each pixel. The tone of eigen pattern consists of two eigen vectors. Since the tone is a ratio of color pixel, the tone eigen vectors can be given by two components of an image. The color component of eigen pattern is represented by three eigen vectors; red, green and blue eigen vectors. The elements of color component eigen vectors are given by the value of red, green and blue components of each pixel, respectively.

2.2 Intensity Eigen Vector

At first, when we denote $I_{\mathrm{int},i}$ as an intensity value of i-th pixel, the intensity value is given by a simple sum or a root mean square of red, green, and blue components,

$$\begin{aligned} I_{\mathrm{int},i} &= R_i + G_i + B_i \\ I_{\mathrm{int},i} &= \sqrt{R_i^{\,2} + G_i^{\,2} + B_i^{\,2}} \end{aligned} \tag{1}$$

where R_i, G_i and B_i represent the value of red, green and blue components of a pixel, respectively. The intensity distribution is represented by I_{int}

$$I_{\mathrm{int}} \in I_{\mathrm{int},i}\ , \quad i = 1,2,3,\cdots, p \tag{2}$$

where p is the number of pixels. Second, I_{int} is normalized with the dynamic range D. The normalized intensity distribution $I_{\mathrm{int}}{}^{D}$ is given by

$$I_{\mathrm{int}}{}^{D} \in \mathrm{Round}\left[D \times \frac{I_{\mathrm{int},i}}{\mathrm{Max}[I_{\mathrm{int}}]} \right], \quad i = 1,2,3,\cdots, p \tag{3}$$

where the functions Round [ ] and Max [ ] work as rounding up to integer number and extracting the maximum value, respectively. Third, the number of pixels having each intensity value from 1 to D is counted. Thereby, the normalized intensity distribution $I_{\mathrm{int}}{}^{D}$ is transformed into a histogram of the intensity distribution. Finally, the intensity eigen vector $\mathbf{E}_{\mathrm{int}}$ is obtained as normalized histogram of intensity value.

2.3 Tone Eigen Vector

The tone is a ratio of red, green and blue components of each pixel. Let us consider the red component of tone distribution. At first, let $I_{\mathrm{tone},R}$ be the red component of tone distribution. Then, the tone distribution is given by

$$I_{\mathrm{tone},R} \in \frac{R_i}{I_{\mathrm{int},i}}\ , \quad i = 1,2,3,\cdots, p \tag{4}$$

Second, $I_{\mathrm{tone},R}$ is normalized with the dynamic range D.

$$I_{\text{tone},R}{}^{D} \in \text{Round}\left[D \times \frac{I_{\text{tone},R,i}}{\text{Max}[I_{\text{tone},R}]} \right], \quad i = 1,2,3,\cdots, p \tag{5}$$

Third, the number of pixels having each tone value from 1 to D is counted. Finally, normalized histogram of each tone value is transformed into the tone eigen vector of red component $\mathbf{E}_{\text{tone},R}$. The other eigen vectors of green $\mathbf{E}_{\text{tone},G}$ and blue $\mathbf{E}_{\text{tone},B}$ are given in much the same way as $\mathbf{E}_{\text{tone},R}$.

2.4 Color Component Eigen Vector

The color component eigen vector is given in terms of the value of red, green and blue components of an image. Let us consider the red component distribution. At first, let $I_{\text{comp},R}$ be the red component distribution. Then, the red component distribution is given by

$$I_{\text{comp},R} \in R_i \,, \quad i = 1,2,3,\cdots, p \tag{6}$$

Second, $I_{\text{comp},R}$ is normalized with the dynamic range D.

$$I_{\text{comp},R}{}^{D} \in \text{Round}\left[D \times \frac{R_i}{\text{Max}[I_{\text{comp},R}]} \right], \quad i = 1,2,3,\cdots, p \tag{7}$$

Third, the number of pixels having each red component value from 1 to D is counted. Finally, normalized histogram of each red component value is transformed into the color component eigen vector of red component $\mathbf{E}_{\text{comp},R}$. The other eigen vectors of green $\mathbf{E}_{\text{comp},G}$ and blue $\mathbf{E}_{\text{comp},B}$ are given in much the same way as $\mathbf{E}_{\text{comp},R}$.

2.5 Eigen Pattern

Let $\mathbf{E}$ be the eigen pattern. Then, $\mathbf{E}$ consists of 6 eigen vectors.

$$\mathbf{E} = [\mathbf{E}_{\text{int}}, \mathbf{E}_{\text{tone},R}, \mathbf{E}_{\text{tone},B}, \mathbf{E}_{\text{comp},R}, \mathbf{E}_{\text{comp},G}, \mathbf{E}_{\text{comp},B}]^T \tag{8}$$

Where T refers to a matrix transpose.

Figure 1 shows sample images and their eigen patterns. Even if an image is transposed, the eigen patterns take the same in value. It is obvious that the eigen pattern removes the location and angle on the screen.

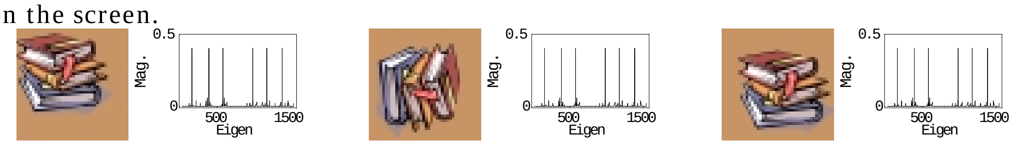
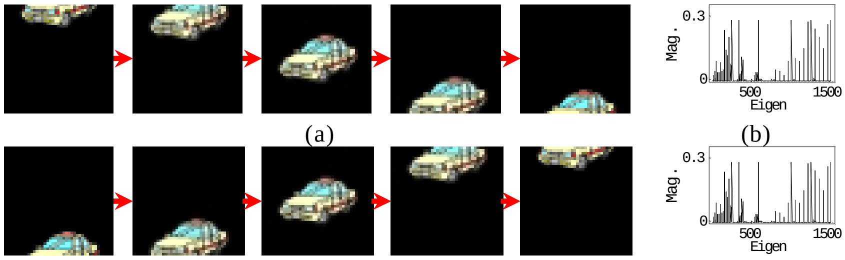


Fig .1 Eigen Patterns of Static Images

2.6 Application to Dynamic Image

Dynamic image is composed of some frame images. Thereby, we have to extract the eigen pattern from the all of frame images, and remove the phase information of dynamic image that same target object shifts different course. Thus, we extract the eigen pattern from the composite image that consists of all of frame images. Since the eigen pattern removes spatial position on the screen, the eigen pattern of composite image removes the phase information of dynamic image.

Figures 2 (a)-(b) shows animation images that same target object shifts different course. Figures 2 (c)-(d) shows their eigen patterns. Both of eigen patterns are same value. It is obvious that the eigen pattern of composite image removes spatial position on the screen as well as phase information of dynamic image.



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

Fig. 2 Eigen Patterns of Dynamic Images
(a)Sample Dynamic Image No.1, (b)Eigen Pattern of (a)
(c)Sample Dynamic Image No.2, (d)Eigen Pattern of (c)

3. Dynamic Image Cognition

3.1 System of Equations by Means of Eigen Patterns

Dynamic image cognition is carried out by means of eigen pattern. After evaluating the eigen patterns of given target images, database is composed by these eigen patterns. Solving linear system of equations using the database makes it possible to cognize the test image. When the database consists of n-th eigen patterns of the image, a system matrix C is obtained by

$$C = [\mathbf{E}_1, \mathbf{E}_2, \mathbf{E}_3 \cdots, \mathbf{E}_n] \tag{9}$$

The subscript of n in (9) refers to an eigen pattern of n-th image. Let $\mathbf{E}_X$ be the eigen pattern of test image for cognizing, then the system of equations is given by

$$\mathbf{E}_X = C \cdot \mathbf{X} \tag{10}$$

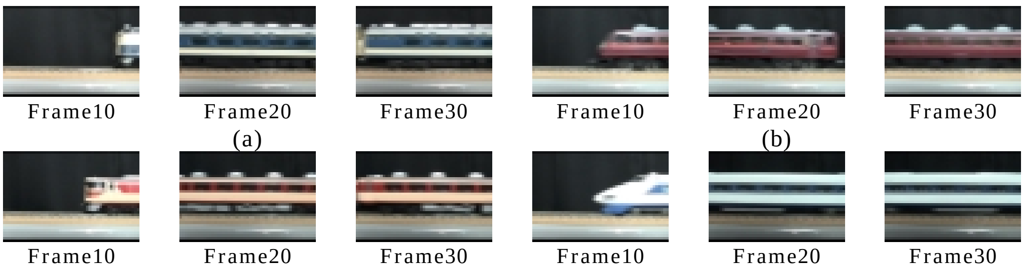
Because of the system matrix C in (9) having n-th columns, the solution vector $\mathbf{X}$ becomes n-th order vector. Since the number of elements of an eigen pattern is much greater than those of the database, then it is possible to apply the conventional least squares (Strang, 1976), namely,

$$\mathbf{X} = [C^T C]^{-1} C^T \mathbf{E}_X \tag{11}$$

When j-th element of solution vector $\mathbf{X}$ in (11) is 1 and the other elements become 0, it is obvious that the test image is the same as the j-th database image. Namely, the test image is cognized as the j-th database image. But, it is rare to obtain such solution vector $\mathbf{X}$, so the element having maximum value in solution vector $\mathbf{X}$ is assumed to be cognized image.

3.2 Example

Figure 3 shows database images. Database images are 4 model trains that have been taken by a digital video camera. The trains in Figure 3 move from right to left.



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

Fig. 3 Database Images
(a)No.1, (b)No.2, (c)No.3, (d)No.4

Figure 4 shows test images. The trains in Figure 4 move from left to right. In this example, we have 4 test images consisting of 30 frame images.

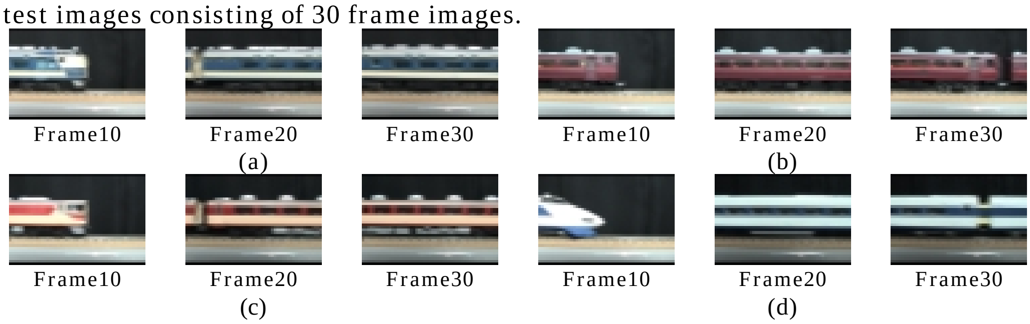


Fig. 4 Test Images
(a)No.1, (b)No.2, (c)No.3, (d)No.4

At first, the eigen patterns of the database images in Figure 3 are calculated. Because of dynamic range D is 256, the system matrix C in (9) has 1536 rows and 4 columns. Second, the eigen pattern of the test image in Figure 4 is calculated to construct an input vector $\mathbf{E}x$. Third, evaluating the solution vector $\mathbf{X}$ by means of (11) carries out the dynamic image cognition. Taking up an element having maximum value in the solution vector $\mathbf{X}$ assumed to be a cognized image as in Figure 5. The horizontal axis in Figures 5 (c1)-(c4) corresponds to database number in Figure 3. It is obvious that we have succeeded in cognizing images.

As a result, the eigen pattern removes the location, angle and size information on the screen, and extracts the essential characteristics of target digital image.

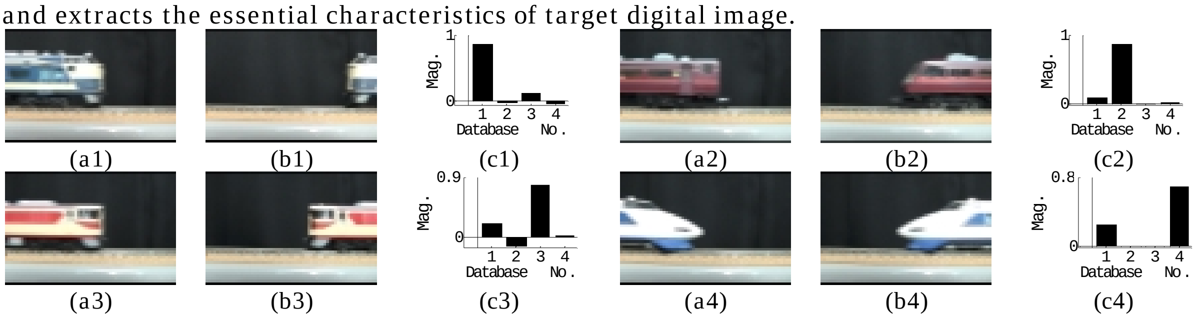


Fig. 5 Cognized Results
(a1)-(a4)Test Images, (b1)-(b4)Cognized Images, (c1)-(c4)Solution Vectors

3.3 Application to Nondestructive Inspection of Electromagnetic Devices

3.3.1 Visualization of Magnetic Field Distribution

Applying our method to visualized magnetodynamic fields is investigated for the nondestructive inspection (Sato et al., 2001). To apply the method to magnetic field, the x, y and z components of measured magnetic fields are respectively projected onto the red, green and blue components to image (Endo et al., 2001). Figure 6 shows the x, y and z magnetic field components and the visualized magnetic field distribution. A position of the pixel corresponds to the measurement point. Thus, it is possible to extract the eigen patterns from the visualized magnetic field distribution as well.

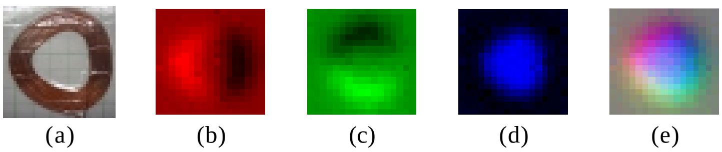


Fig. 6 Magnetic Field Components and Visualized Magnetic Field Distribution as a Color Image
(a)Coil element, (b)x component, (c)y component, (d)z component, (e)Visualized Magnetic Field Distribution

3.3.2 Cognition of Magnetic Devices

Figure 7 shows the visualized magnetic field distributions for database. Database is composed of magnetic devices such as inductors and transformers. In this example, we have 25 database images.

Figure 8 shows the test images. Test images are compressed to the vertical as well as horizontal directions.

Figure 9 shows cognition results. As a result, we have succeeded in cognizing each of the magnetic devises without any decomposition. Thus, this methodology is one of the most powerful and effective nondestructive inspections of electromagnetic devices.

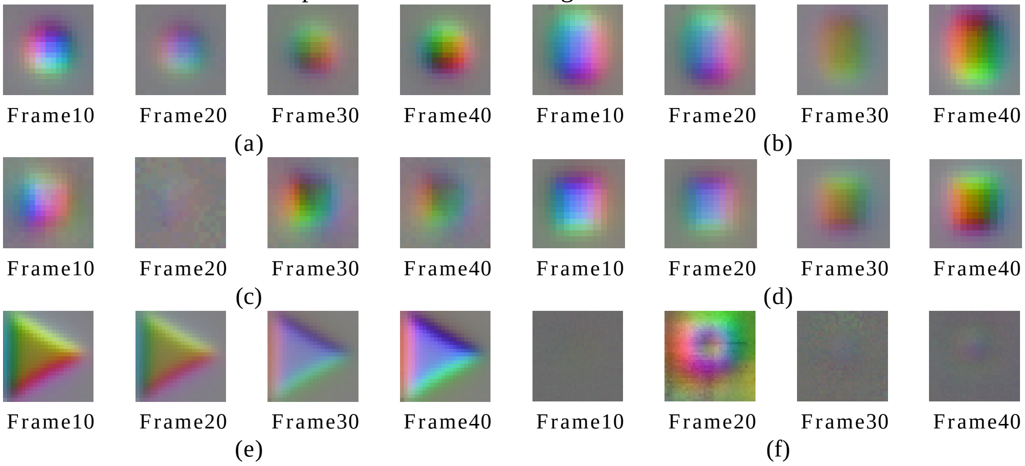


Fig. 7 Database Images
(a)No.1 (17-17pixels), (b) No.2 (17-17pixels), (c)No.3 (17-17pixels), (d)No.23 (15-15pixels), (e)No.24 (24-24pixels), (f)No.25 (35-35pixels)

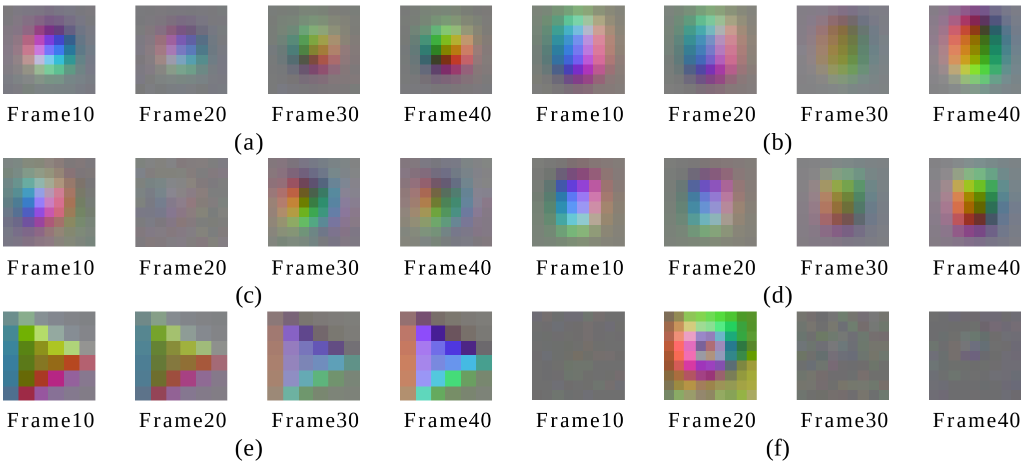


Fig. 8 Test Images
(a)No.1 (9-9pixels), (b) No.2 (9-9pixels), (c)No.3 (9-9pixels), (d)No.23 (8-8pixels), (e)No.24 (6-6pixels), (f)No.25 (7-7pixels)

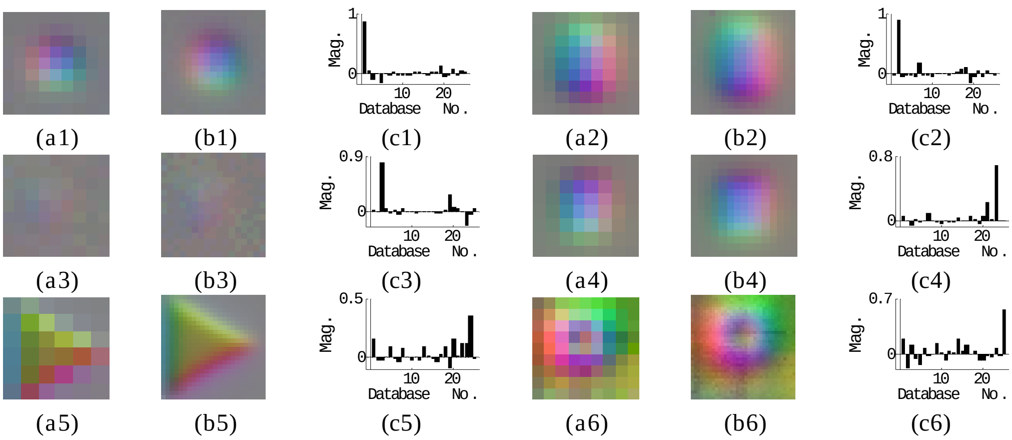


Fig. 9 Cognized Results
(a1)-(a6)Test Images, (b1)-(b6)Cognized Images, (c1)-(c6)Solution Vectors

Figure 10 shows comparison between dynamic image cognition and static image cognition. Solution vectors of static image cognition in Figures 10 (b1)-(b6) are entirely small in value compared with dynamic image cognition in Figures 10 (a1)-(a6). In case of Figures 10 (b5)-(b6), the static image cognition has not distinguished the correct ones. From the results in Figure 10, our dynamic image cognition approach gives more reliable solution.

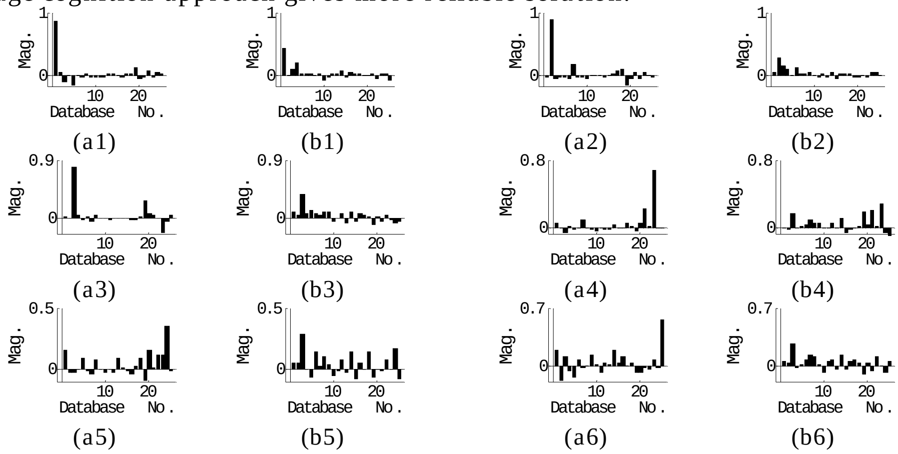


Fig. 10 Comparisons between Dynamic Image Cognition and Static Image Cognition
(a1)-(a6)Dynamic Image Cognition, (b1)-(b6)Static Image Cognition

4. Conclusion

In this paper, we have proposed the eigen pattern of visualized information in order to extract the essential characteristics of digital images. The eigen pattern removes the location, angle and size information on the screen. This eigen pattern methodology is generalized to the dynamic digital image. We have extracted the eigen pattern from the composite image that consists of all of frame images in order to remove the phase information of dynamic image. As an example, we have applied our method to nondestructive inspection of electromagnetic devices. Consequently, we have succeeded in cognizing each of the magnetic devises without any decomposition.

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