Application of CIELuv Color model for Color Pattern Recognition by Simulated Annealing

Yiting Tsai, Chulung Chen*, Wanyi Chen, Chonyu Wang, Chunyi Hu

***Abstract*—This research uses the concept of simulated annealing to design the near optimal quantized reference function. We transform a color image into three CIELuv color space components for identifying the different views of the target. The system yields one reference function by minimum average correlation energy method. Then we apply simulated annealing in Mach-Zehnder joint transform correlator. From simulation results, the optoelectronic pattern recognition system with simulated annealing algorithm shows a good optimization capability.**

***Index Terms*—simulated annealing, CIELuv color space.**

I. Introduction

Optical pattern recognition is an important part of optical data processing. Correlation filter has the properties of shift invariance. In 1964, VanderLugt [1] proposed the concept of matching spatial filter device. It requires a complex filter prefabricated in Fourier space for different test images and needs accurate realignment along the optical axis. In 1966, Weaver and Goodman [2] proposed the joint transform correlator (JTC). Compared with the VanderLugt correlator, the optical structure is less complicated. The target image and reference image are exhibited side by side at input plane without accurate problem. There is the energy of zero-order term in the JTC structure. It will influence the detected signal exactness. In 1995, Lu [3] and other four people proposed phase shift method, which successfully yielded nonzero order joint transform correlator (NOJTC). The system is better than the classical JTC. In this paper, the Mach-Zehnder JTC (MZJTC) [4] can accomplish the removed zero order term removal in only one step directly without storing the Fourier spectra of both the reference and target images beforehand. On the other hand, the minimum average correlation energy (MACE) based on Lagrange multipliers technique to minimize the average correlation plane energy has been adopted [5-7]. It can increase the output correlation peak sharpness, and the sidelobes will be relatively reduced. In 1983, Kirkpatrick et al. [8] proposed simulated annealing (SA) and successfully applied it in combinatorial optimization problems. The most obvious characteristics of the algorithm is based on using some criteria to judge the objective function to avoid falling into local optimal solution and achieve convergence. In this research, we use MACE method to yield the first reference function. And then we utilize the convergence properties of SA, which minimizes the correlation plane energy in order to yield near optimal quantized reference function applied in MZJTC.

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II. Analysis

RGB color model is used widely and is easy to understand. It consists of the red, green and blue respectively. However, CIELuv color model is one attempt at providing a perceptually uniform color space. It transform RGB source into one luminance and two chrominance components by linear conversion. The relationships between RGB and CIELuv are shown below [9].

$$L^* = \begin{cases} 116 \cdot \left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} - 16, & \frac{Y}{Y_n} > \left(\frac{6}{29}\right)^3 \\ \left(\frac{29}{3}\right)^3 \frac{Y}{Y_n}, & \frac{Y}{Y_n} \le \left(\frac{6}{29}\right)^3 \end{cases}.$$
$$u^* = 13L^* \cdot (u' - u_n').$$
$$v^* = 13L^* \cdot (v' - u_n'). \tag{1}$$

where

$$u' = \frac{4X}{X+15Y+3Z}.$$
$$v' = \frac{4X}{X+15Y+3Z}. \tag{2}$$

The Mach-Zehnder JTC (MZJTC) can accomplish the removed zero order removal processing in only one step directly in Fig. 1. A laser is used to be the light source. That consists of Fourier lens, reflective liquid crystal spatial light modulator (RLCSLM) and CCD to perform the optical pattern recognition. We define the position functions of reference and target images on the input planes. There are three grayscale images t_l, t_u and t_v,, is mached to the l, u and v channels of the target image. Analogously, another three grayscale images h_l, h_u and h_v, corresponds to the l, u and v channels of the reference image. The arrangement of input plane in RLCSLM1 and RLCSLM2 are shown in Figs.2. The reference and target image channels placed on the RLCSLM1 and RLCSLM2 respectively can be expressed as

$$t = \sum_{n=1}^{3} t_n(x-d, y+a_n), \tag{3}$$

and

$$h = \sum_{m=1}^{3} h_m(x+d, y+a_m). \tag{4}$$

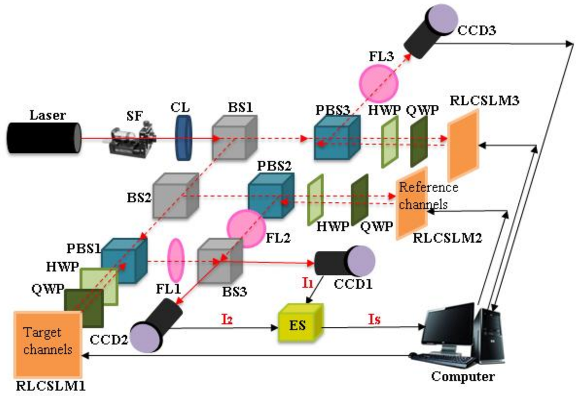

Fig. 1 The structure of a MZJTC system.

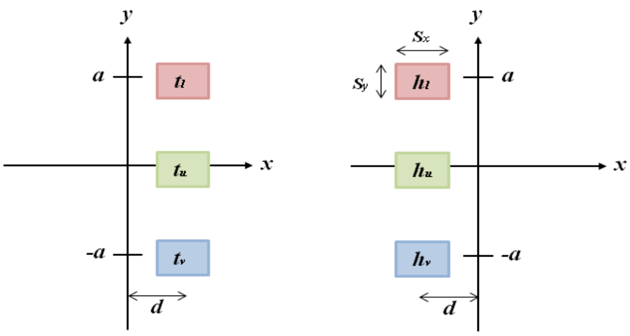

Fig. 2 Arrangement of RLCSLM1 for target channels (left)

and Arrangement of RLCSLM2 for reference channels (right).

Both lights occur fractional reflection and transmission at BS3. Joint transform power spectrums (JTPSs) of two light fields will be detected by CCD1 and CCD2. We connect the outputs to the electronic subtractor (ES) to remove the zero order term as

$$I_S = I_1 - I_2 = |E_2(u,v)|^2 - |E_1(u,v)|^2. \quad (5)$$

by Stokes relations, we obtain the equation $\gamma_2 = -\gamma_1$. Let $|\gamma_1| = |\tau_1|$ and $|\gamma_2| = |\tau_2|$, then rewrite the Eq. (5) as

$$I_S = 2|\gamma_1^*\tau_2 - \tau_1^*\gamma_2| \cdot \sum_{m=1}^{3}\sum_{n=1}^{3}|H_m(u,v)||T_n(u,v)| \cdot \cos\{2\pi[(z_m - z_n)v + 2du] + \theta + \theta_{H_m}(u,v) - \theta_{T_n}(u,v)\}. \quad (6)$$

where θ is the phase of $\tau_2\gamma_1{}^* - \tau_1{}^*\gamma_2$, θ_{H_m} and θ_{T_n} are denote the phase of $|H_m(u,v)|$ and $|T_n(u,v)|$ respectively. The zero order term is removed. I_s is called Mach-Zehnder JTPS (MZJTPS). Then we sent the MZJTPS to RLCSLM3. With inverse Fourier transforming by FL3, the cross-correlation output will be obtained in CCD3 as follows:

$$o(x,y) = \sum_{m=1}^{3}\sum_{n=1}^{3} c_{mn}(-x,-y) \otimes \delta(x + 2d, y - z_m + z_n)\exp(-j\theta) \quad (7)$$
$$+ \sum_{m=1}^{3}\sum_{n=1}^{3} c_{mn}^*(x,y) \otimes \delta(x - 2d, y + z_m - z_n)\exp(j\theta)$$

Here the symbols $\otimes$ and $\circ$ represent the convolution and correlation operations.

I. Simulation Methods and Procedures

In this research, we choose a colorful ladybug pattern with 64*64 pixels as the original image. It is shown in Fig. 3.

Fig. 3 Original target image.

The original pattern is rotated form -16^{o} to 16^{o} in steps of 2 ^{o} to yield 17 training images. Each training image is decomposed into 3 pieces with L, u and v color space, as shown in Fig.4. Then we obtain 3 groups of training images with 17 different angles. It is the preparation for simulated annealing (SA) procedure. We utilize the global convergence property of SA to seek better reference functions that increase the ability of recognition system.

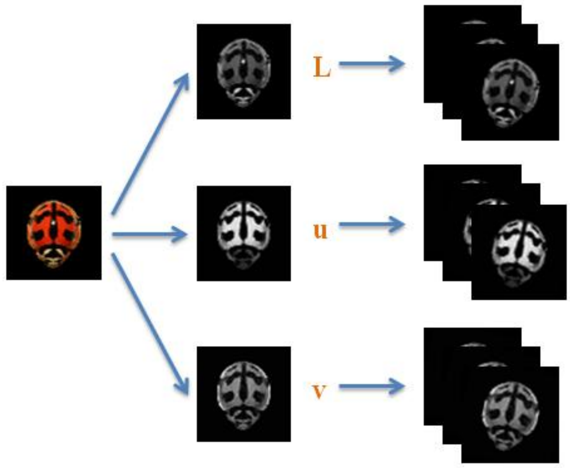

Fig. 4 Luv components of training patterns.

Generally, the initial solution of SA is given randomly. In this study, we try to use difference conditions. The reference function is generated with the training images by MACE filter and then directly quantized. Here, we use correlation to peak energy (CPE) [10] as the energy function. CPE is the ratio between total correlation energy of output plane and the primary correlation peak energy. It is given by

$$\text{CPE} = \frac{\sum_{x,y}|c(x,y)|^2}{|c(0,0)|^2}. \quad (8)$$

The detail of the SA algorithm is described as following steps.

1. Utilize MACE algorithm to yield a 3-level (1, 0, -1) reference function.
2. Calculate CPE_i for each training image, and the sum of CPE_s as the energy function. Which is expressed as

$$E_{old} = \sum_{i=1}^{N} CPE_i^2 \quad (9)$$

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where i represents the i-th training images corresponding to the value of CPE.

3. CPI initially set a minimum value of 0. Change a single pixel level of the reference function $r(x, y)$, then find out the new target function E_{new} .
4. Whether new target function is smaller than the original target function. ; After the operation and whether the minimum CPI increase.
5. Find the difference value of the object function ΔE . It is defined as
6.

$$\Delta E = E_{new} - E_{old} \tag{10}$$

7. If $\Delta E \leq 0$, then accept the level as the new reference function $r(x, y)$, E_{new} as the system temperature T of the next algorithm, and the initial point E_{old}. If $\Delta E > 0$, then the use $p(\Delta E)$ to calculate the acceptance probability of a new level, and $p(\Delta E)$ is defined as

$$p(\Delta E) = \exp(-\frac{\Delta E}{kT}). \tag{11}$$

Here T is control parameter of SA, which directly control optimization direction of the system, k is the lower the temperature coefficient. Set r as the random number generated in [0, 1] by computer.

8. If $p(\Delta E) \geq r$, accept the new level, which updates the reference function $r(x, y)$, E_{new} as the system temperature and the initial point E_{old} of the next algorithm. Or $p(\Delta E) < r$, then give up the new level, still using the original level and E_{old} as the initial point of the next algorithm. If all pixels are changed, then go to the next step. Otherwise, change the next pixel of $r(x, y)$ and find the E_{new}.
9. Record the value of object function collectively referred to as Energy. When normalized standard difference of last 10 times Energy is less than 0.03, then stop the operation. Otherwise reduce the $kT = 0.9kT$, and back to step 3.
10. Repeat the above steps were calculated reference image L, u, and v each situation, level number gradually increased, as shown below:
    3 levels：-1、0、1,
    5 levels：-2/2、-1/2、0、1/2、2/2,
    9 levels：-4/4、-3/4 ~ 0 ~ 3/4、4/4,
    17 levels：-8/8、-7/8 ~ 0 ~ 7/8、8/8,
    65 levels：-32/32、-31/32 ~ 0 ~ 31/32、32/32,
    129 levels：-64/64、-63/64 ~ 0 ~ 63/64、64/64.

II. Results

We use MZJTC for optical cross-correlation operation, finally it can obtain cross-correlation of energy distribution operations of reference function and target image in the output plane. In this experiment of higher level number, the convergent curve is relatively smooth. Moreover, the more the level number is, the lower the beginning cost function will be. The terminative condition is set to be within the last 10 cycles. At this moment, we consider that the cost function probably reach the global convergence. Hence, the program stops computing as soon as the normalized standard deviation satisfies the pre-set condition. From the Simulation, it concluded that the level higher, energy distribution would be sharper and its sidelobes would be smaller in the output plane in Fig. 5.

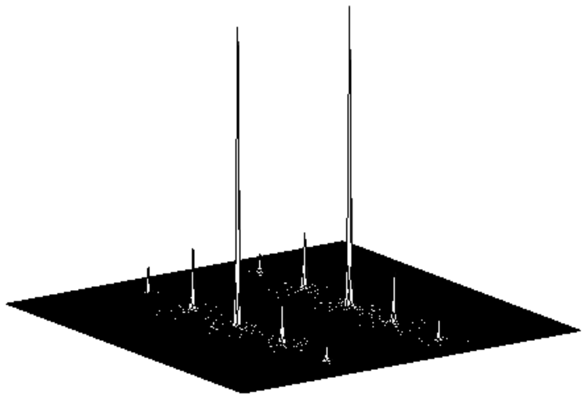

Fig. 5 The correlation energy of 129 levels on the output plane.

The CPI is the highest correlation energy on the output plane; it is the main index for tracking target image. Fig. 7 shows the CPI against different rotation angles with level 129. There are 3 curves in each figure, the CPI against rotated training image, non-training image and non-target image. Fig. 6 displays the non-target image. We rotate the non-target image from -16° to 16° in steps of 2°, to generate 17 training images as the same as the original image. The original image is rotated from -15° to 15° in steps of 2° to be 16 non-training images. The x-axis represents the rotation angle of the training images, and the y-axis represents the CPI.

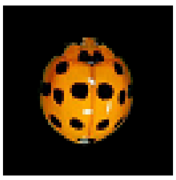

Fig. 6 Non-target image

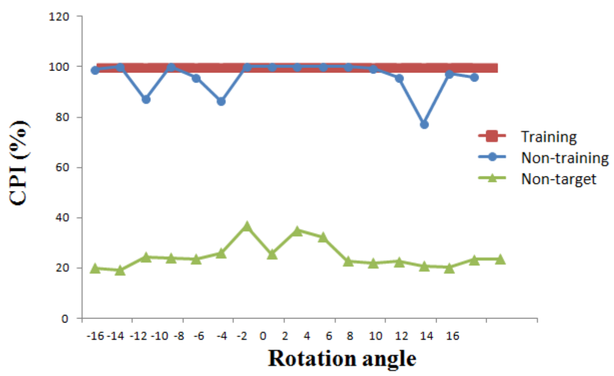

Fig. 7 CPI against rotation angles with 129 levels.

Fig. 8 shows the PSR against different rotation angles with level 129. These curves are almost concave down. It means that the recognition ability of the filter gradually

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decreases with the increasing rotation angle of the target image.

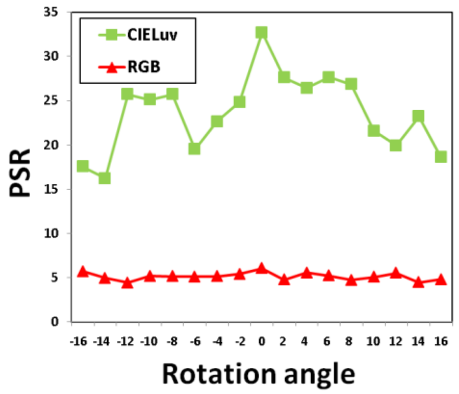

Fig. 8 PSR against rotation angles with 129 levels.

Average PSR (APSR) is the average of PSR computed by filter for each angle of training images. Figure 9 displays the curve of each level number corresponding to the APSR. According to variation of the curve in Fig.9 , we see that APSR shows an increasing tendency with the increasing level number of the filter. In other words, while we adopt higher level number of filter, the capability of recognition is relatively better. Additionally, it is important to note that the recognition ability of the multi-channel correlator on CIELuv color space is significantly superior to that on RGB color space.

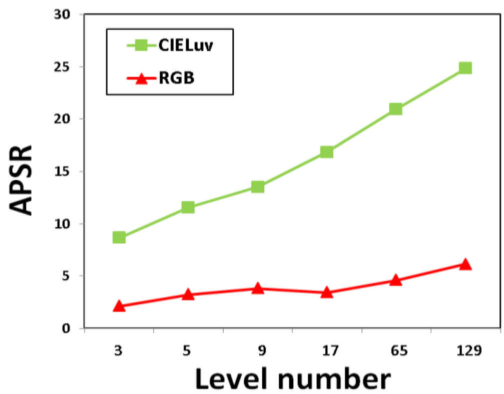

Fig. 9 The APSR corresponding to each level number.

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