Optoelectronic Pattern Recognition Based on YUV Color Model with Shifted Training Images and Liquid Crystal Spatial Light Modulator

Yuezhe Li, Chulung Chen*, Yachu Hsieh, Hsinyi Chen

***Abstract*—This research uses minimum average correlation energy method and shifted training images to recognize the polychromatic images based on YUV model. In our former research, the training images are displayed at the center position. However, the total side lobe energy may not be the minimum. In order to solve the problem, we transform the color image into three YUV color space components. Then, three components are rotated from 0° to 360° in steps of 5° and shifted from -5 to 5 pixels in both of vertical and the horizontal directions to yield training images. Finally, we can choose the filter with minimum side lobe energy on the output plane by using the minimum average correlation energy method. Therefore, we can enhance the efficiency of recognition and decrease the possibility of false recognition.**

***Index Terms*—Minimum average correlation energy, training image, YUV color model**

I. Introduction

Recently, the optical correlation has been widely utilized in pattern recognition. In 1964, VanderLugt proposed the VanderLugt correlator (VLC) [1] for pattern recognition. However, the VLC system is difficult to be accurately aligned along the optical axis. To improve this problem, Weaver and Goodman proposed joint transform correlator (JTC) [2] in 1966. Due to the lack of proper operating device, JTC was substantially stagnant until the real-time programmable JTC was proposed by Yu and Lu in 1984 [3]. JTC system put the reference and target images on the input plane simultaneously to improve the problem of alignment. Nevertheless, the classical JTC has the strong zero order term on the output plane, which yields the recognition capability poorly. The phase shifting technique and joint transform power spectrum (JTPS) subtraction were proposed to remove the zero order term [4], [5]. On the other hand, the Mach-Zehnder JTC (MZJTC) [6], [7] can accomplish the removed zero order term processing just in only one step directly. The location and orientation of target are often unknown for real application. Chen et al. [9] utilized the minimum average correlation energy (MACE) method based on the Lagrange multipliers to design the reference function. A polychromatic pattern recognition system based on MZJTC was later introduced [8].

For example, in additive color systems, yellow is a combination of red and green. Therefore, RGB signals are usually coupled to each other. The YUV model defines a color space in terms of one luma (Y) and two chrominance (UV) components. In general, the 3 components are generally independent. In the paper, we will use MACE as well as shifted training images to study the performance for image recognition based on YUV color model in the MZJTC system.

II. Analysis

A spatial reference function is designed to deal with various distortions and to reduce the correlation sidelobes. We assume that there are N training images spanning the desired distortion-invariant feature range. The MZJTC system is based on a Mach-Zehnder structure, which includes an electronic subtractor (ES), as shown in Fig. 1. It contains 3 RLCSLM and 3 CCD cameras.

In our MZJTC system, a color space used in image science is the YUV components, not the red, green, and blue (RGB) color space. In our MZJTC system, a color space used in image science is the YUV components, not the red, green, and blue (RGB) color space. The Y channel represents the luminance of the color while the U and V channels are jointly related to the hue and saturation attribute to a color. This model is compatible with monochrome television standards. We can transfer the RGB to YUV color space as the following equations:

$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.147 & -0.289 & 0.436 \\ 0.615 & -0.515 & -0.100 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}. \qquad (1)$$

From Eq. (1), the Y channel includes all the information necessary for the monochromatic television. It is equivalent to our perception of the relative brightness of different colors. The transformation matrix above indicates respective weights of red, green, and blue. We can retain the same perception of brightness by using these weights when converting a color image to grayscale in our MZJTC system.

We put the reference images $h = \sum_{m=1}^{3} h_m(x+d, y+z_m)$ (m=Y, U, V or 1, 2, 3) and target images $t = \sum_{n=1}^{3} t_n(x-d, y+z_n)$ (n=Y, U, V or 1, 2, 3) into RLCSLM1 and RLCSLM2, respectively as shown in Fig. 2. After a collimated coherent laser beam passes through the

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Fourier lens and illuminates the beam splitter 3 (BS3), we can represent the light fields E_1 and E_2 that include the reflected and transmitted components as follow:

$$E_1(u,v) = \sum_{m=1}^{3} \tau_1 \cdot H_m(u,v) \cdot exp^{j2\pi(du+z_m v)} + \sum_{n=1}^{3} \gamma_2 \cdot T_n(u,v) \cdot exp^{-j2\pi(du-z_n v)} \quad (2)$$

$$E_2(u,v) = \sum_{m=1}^{3} \gamma_1 \cdot H_m(u,v) \cdot exp^{j2\pi(du+z_m v)} + \sum_{n=1}^{3} \tau_2 \cdot T_n(u,v) \cdot exp^{-j2\pi(du-z_n v)} \quad (3)$$

Here d and m are the distances of the reference channel and target channel away from the vertical and horizontal central lines of the RLCSLM1 and RLCSLM2, respectively, and (u,v) is the spatial frequency coordinate of the Fourier plane; γ and τ denote the reflection and transmission coefficients of the BS3, respectively; $H(u,v)$ and $T(u,v)$ are the Fourier transforms of $h(u,v)$ and $t(u,v)$, respectively. Both of the outputs of CCD1 and CCD2 are connected to an ES. The resultant output of the ES due to the square-law detection is

$$\begin{aligned} I_s(u,v) &= |E_2(u,v)|^2 - |E_1(u,v)|^2 \\ &= (|\gamma_1|^2 - |\tau_1|^2)\cdot \sum_{m=1}^{3}\sum_{m'=1}^{3} H_m(u,v)\, H^*{}_{m'}(u,v) \cdot exp^{j2\pi\left(z_m - z_{m'}\right)v} \\ &+ (|\tau_2|^2 - |\gamma_2|^2)\cdot \sum_{n=1}^{3}\sum_{n'=1}^{3} T_n(u,v)\, T^*{}_{n'}(u,v) \cdot exp^{j2\pi(z_n - z_{n'})v} \\ &+ (\tau_2\gamma_1{}^* - \tau_1{}^*\gamma_2)\cdot \sum_{m=1}^{3}\sum_{n=1}^{3} H_m(u,v)\, T^*{}_n(u,v) \cdot exp^{j2\pi[(z_m - z_n)v + 2du]} \\ &+ (\tau_2{}^*\gamma_1 - \tau_1\gamma_2{}^*)\cdot \sum_{m=1}^{3}\sum_{n=1}^{3} H^*{}_m(u,v)\, T_n(u,v) \cdot exp^{-j2\pi[(z_m - z_n)v + 2du]} \end{aligned} \quad (4)$$

By the Stokes relations [10] $\gamma_2 = -\gamma_1$. We further let $|\gamma_1| = |\tau_1|$ 、 $|\gamma_2| = |\tau_2|$. Therefore,

$$I_s = 2|\tau_2\gamma_1{}^* - \tau_1{}^*\gamma_2| \cdot \sum_{m=1}^{3}\sum_{n=1}^{3} |H_m(u,v)||T_n(u,v)| \cdot cos\{2\pi[(z_m - z_n)v + 2du] + \theta + \theta_{H_m}(u,v) - \theta_{T_n}(u,v)\} . \quad (5)$$

Here θ is the phase of $\tau_2\gamma_1{}^* - \tau_1{}^*\gamma_2$; θ_{H_m} and θ_{T_n} are the phases of $H_m(u,v)$ and $T_n(u,v)$, respectively. Finally, we can obtain the joint transform power spectrum (JTPS) without zero order. Then we put I_s into RLCSLM3. Via the CCD3 detector, we can obtain the intensity distribution at the output plane, which is

$$o(x,y) = \sum_{m=1}^{3}\sum_{n=1}^{3} c_{mn}(-x,-y) \otimes \delta(x + 2d, y - zm + zn) exp^{(-j\theta)} + \sum_{m=1}^{3}\sum_{n=1}^{3} c^*{}_{mn}(x,y) \otimes \delta(x - 2d, y + z_m - z_n) exp^{(j\theta)}. \quad (6)$$

Here $C_{mn} = h_m(x,y) \circ t_n(x,y)$ is the cross correlation between h_m and t_n; $\circ$ and $\otimes$ denote the correlation and convolution operators, respectively.

III. Numerical Results

In this work, we chose a colorful fish with 64 × 64 pixels to be the original pattern, as shown in Fig. 3. First, the training image set contains 72 images with different rotation angles from 0^o to 355^o (in steps of 5^o). The reference images are synthesized by the shifted training images (from -5 to 5 pixels in both of vertical and the horizontal directions). Subsequently, we utilize training set images with different rotation angles to be the target images for the image recognition test. The comparison of the CPI versus the rotation angle from 0° to 355° is shown in Fig. 4 when the test pattern is the target. We can observe that the correlation peak intensity (CPI) is 100% by using the training image. The CPI curve for the non-training angle image fluctuates between values of 85-100%. Each CPI can achieve over 85%. We also record the results of PSR (peak to secondary intensity ratio) for each target and compare the results between the original and shifted training images, as shown in Fig. 5. Each PSR is always higher than 2. It means that shifted image can yield nice recognition ability.

IV. Conclusion

In this work, we have proposed MZJTC based on the YUV color model with the shift image method, which offers a way for polychromatic pattern recognition. This system could remove the zero order term in only one step. Besides, we have demonstrated that the designed reference function is a real-valued function, and we utilize some RLCSLM devices to achieve real-valued only modulation. The nice results can be found for shifts in rotated training image.

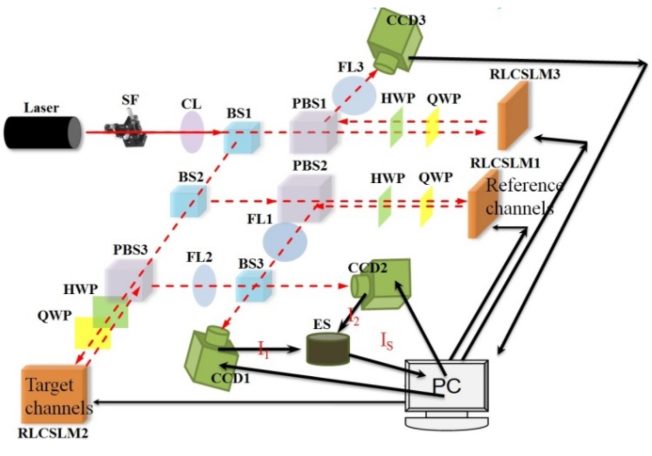

Fig. 1 The structure of MZJTC system.

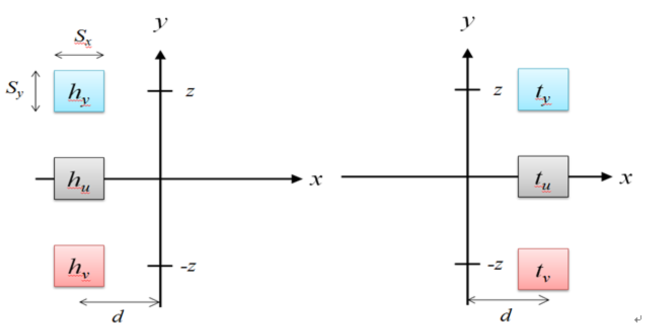

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Fig. 2 The MZJTC input plane of Y, U, V three components arranged in the reference and target images. Left: RLCSLM1 and right: RLCSLM2

Fig.3 The original target image.

REFERENCES

[1] A. VanderLugt, "Signal detection by complex spatial filtering," *IEEE Transactions on Information Theory*, **10**, 139-145, (1964).
[2] C. S. Weaver and J. W. Goodman, "A technique for optically convolving two functions," *Applied Optics*, **5**, 1248-1249, (1966).
[3] F. T. S. Yu and X. J. Lu, "A real-time programmable joint transform correlator," *Optics Communications*, **52**, 10-16, (1984).
[4] B. Javide and J. Wang, "Quantization and truncation effects on binary joint transform correlation," *Optics Communications*, **84**, 374-382 (1991).
[5] C. J. Cheng and H. Y. Tu, "Implementation of a nonzero-order joint transform correlator using interferometric technique," *Optical Review*, **9**, 193-196 (2002).
[6] C. Chen*, J. Fang, "Cross-correlation peak optimization on joint transform correlators," *Optics Communications*, **178**, 315-322 (2000).
[7] C. Chen, C. Chen, C. Lee, and C. Chen, "Constrained optimization on the nonzero-order joint transform correlator constructed with the Mach-Zehnder configuration, " *Optics Communications*, **231**, 165-173, (2004).
[8] C. Lee, C. Chen, C. Wang, and C. Chang, "An Image-encoded Mach-Zehnder Joint Transform Correlator for Polychromatic Pattern Recognition with Multi-level Quantized Reference Functions, " *IMECS*, **I**, 19-21 (2008).
[9] A. Mahalanobis, B. V. K. V. Kumar, and D. Casasent, "Minimum average correlation energy filters," *Applied Optics*, **26**, 3633-3640, (1987).
[10] E. Hecht, "Optics, " *Reading, Mass. 4th edition, Addison-Wesley*, 136-137 (2002).

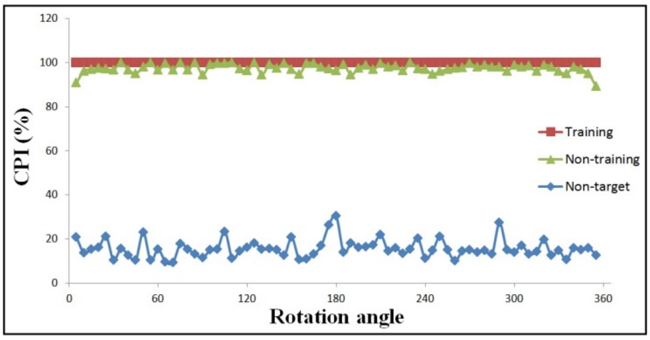

Fig. 4 CPI versus rotation angle from 0° to 355°.

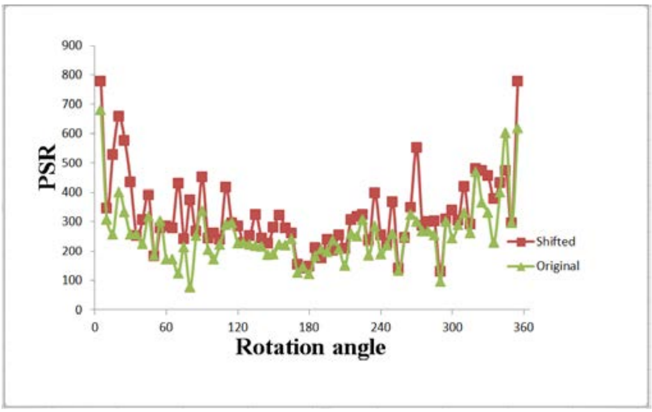

Fig. 5 PSR versus rotation angle from 0° to 355°.

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