Optoelectronic Training Architecture for Supervised Filtering Technique

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***Abstract*— Supervised filtering technique is a kind of dynamic neural network that performs one filter mask and one bias value which are adjustable by a supervised learning algorithm for various types of applications. Training procedure for a supervised filtering technique needs much more computation and complexity for 2D data set compare to test procedure. Therefore, optoelectronic architecture has been developed for training procedure that presents high speed application possibility in hardware and incorporation availability with other optical systems. In optoelectronic architecture, we have employed Joint Transform Correlator (JTC) which produces same results with convolution operation when mask coefficients are symmetric. For image processing applications, mask coefficients should be optimized according to input and desired output images. This task is realized by supervised training stage based on the proposed optoelectronic architecture. In test stage, we have verified the proposed optoelectronic training architecture for image corner detection problem.**

Keywords*— *Optoelectronic computing, Joint Transform Correlator, Supervised filter, Optic image processing.

I. INTRODUCTION

Over the last few decades, a number of optical neural network systems have been exploited for various applications [1-4]. Implementation of optical neural networks is an attractive issue due to available scope of massive interconnection and two-dimensional parallel data processing. Recently, optical implementation of image feature extraction and filtering techniques using cellular neural networks, wavelet transform and supervised filtering techniques have been proposed [3-6]. Supervised filtering technique has been found attractive for various image processing applications such as fingerprint enhancement and identification, image feature extraction and processing [4, 7]. However, there are a few optical implementations for neural network's training process in the literature [8]. Training process requires 100-1000 iterations while the test process requires only 1 iteration. Therefore, a new optoelectronic supervised learning algorithm has been developed using the theory of Fourier optics and phase-only joint transform correlator (POJTC).

In the optical implementation, filter coefficients and data realization problems are encountered due to negative values. To alleviate this type of problem, recently phase-only joint transform correlator technique has been reported in which both the input and Fourier planes are phase-encoded [5]. The phase-only JTC yields similar results as the amplitude only JTC. However, it allows encoding of bipolar data (including positive and negative values) in the input unlike the amplitude-only JTC. This feature is attractive for the applications of correlation operation in case of bipolar data, such as filtering applications [4-6].

II. SUPERVISED FILTERING TECHNIQUE

The supervised filtering (SF) technique is shown in Fig.1 and can be determined mathematically as follows,
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$$a_{m,n}(t+1) = \varphi\left[\underbrace{\left(\sum_{i=-s}^{s}\sum_{j=-s}^{s} h_{i,j}\, a_{m+i,n+j}(t)\right) + b}_{c(t)}\right] \tag{1}$$

where $h_{i,j}$ is a filter mask which is designed at size of $s \times s$, b is scalar bias value, t is the iteration step, and $a_{m,n}(t+1)$ and $a_{m,n}(t)$ are output and input images of system, respectively.

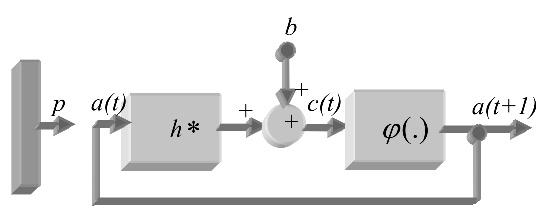


Fig.1. Supervised filtering architecture

Initially, the input image is defined as $a_{m,n}$ *(0) = p*. The activation function φ is a piecewise linear or nonlinear threshold function. In the training step, the error function between desired output and actual output images is minimized using Widrow learning algorithm. For supervised filtering system, error function can be defined as,

$$E(h,b)=\frac{1}{2}\sum_{m}\sum_{n}(a_{m,n}(t+1)-d_{m,n})^2 \tag{2}$$

where $a_{m,n}(t+1)$ is actual output and $d_{m,n}$ is desired output image. After error minimization in the each iteration, new updated filter coefficients become equivalent to,

$$h(t+1)=h(t)-2\,\eta\; a(\infty)\,E(h,d) \tag{3}$$

where $a(\infty)$ denotes stable output and η represents learning rate. Stable output is defined that each output pixel value belongs to $\{-1,1\}$. At first, Eq. (1) runs until produce stable output as $a_{m,n}(t+1)\rightarrow a_{m,n}(\infty)$. Then, updated filter coefficients are obtained by Eq. (3). If these filter coefficients provide the minimum error defined in Eq. (2), training process is completed. Otherwise, above steps repeat to find final filter coefficients.

III. Optoelectronic Training Architecture

Converging to $a_{m,n}(t+1)\rightarrow a_{m,n}(\infty)$ requires so many 2D cross-correlation due to c(t) in Eq. (1). This operation can be realized by using optoelectronic architecture of joint transform correlator as shown in Fig. 2.

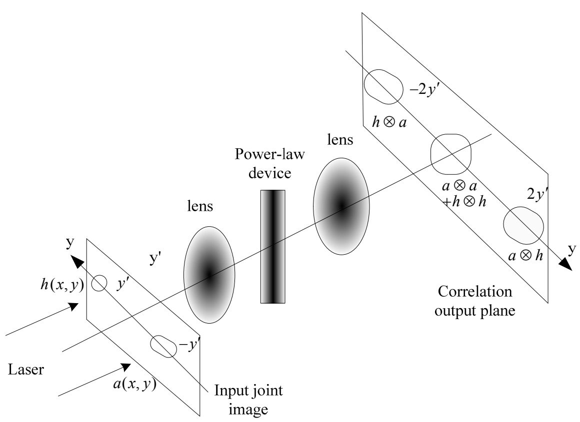


Fig. 2 Joint transform correlator architecture.

Input joint image in the JTC involving filter mask $h\;(x,y+y')$ and input image $a(x,y-y')$ can be defined as,

$$c(x,y)=h(x,y+y')+a(x,y-y') \tag{4}$$

The correlation output for this input joint image is obtained by following equation,

$$\begin{aligned}c'(x,y)=&\; h(x,y)\otimes h(x,y)+a(x,y)\otimes a(x,y)\\ &+h(x,y)\otimes a(x,y)*\delta(y+2y')\\ &+a(x,y)\otimes h(x,y)*\delta(y-2y')\end{aligned} \tag{5}$$

where '∗' denotes a convolution operation. The last two terms are the cross-correlations of *h(x,y)* with *a(x,y)*. This is precisely the definition of the first term of SF as *a(x,y)* with respect to *h(x,y)* in Eq. (1). To encode the bipolar data of $h\;(x,y+y')$ and $a(x,y-y')$ in the input and Fourier plane, the POJTC is employed. Assuming the input image is *r(x,y),* the phase-transformed is described as follows,

$$r_1(x,y)=\exp[\,jAr(x,y)] \tag{6}$$

where *A* is the phase-depth of the phase-modulated SLM and represents an intensity-to-phase conversion. The Fourier plane field is represented as follows

$$\begin{aligned}U_j\;\alpha\;F\{\exp[\,j\,A\,r(x,y)]\}&=F\left\{\sum_n\frac{(jA)^n}{n!}[r(x,y)]^n\right\}\\ &=\sum_n\frac{(jA)^n}{n!}F\{[r\;(x,y)]^n\}\end{aligned} \tag{7}$$

Defining $C_n=(jA)^n/n!$ and $F\{r^n\}=R^n$ and squaring the Fourier plane, the joint power spectrum is expressed as,

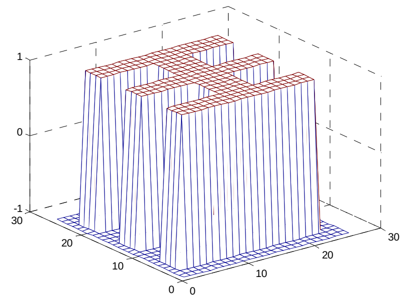
$$\begin{aligned}\left|U_j\,(u,v)\right|^2\alpha\sum_{n,m}C_nC_m^*\left[R(u,v)^{*^n}\right]\\ \times\left[R(u,v)^{*^m}\right]\end{aligned} \tag{8}$$

where *u* and *v* are the spatial frequencies associated with the *x* and *y* directions. Applying a Fourier transform again, correlation plane intensity is obtained as,

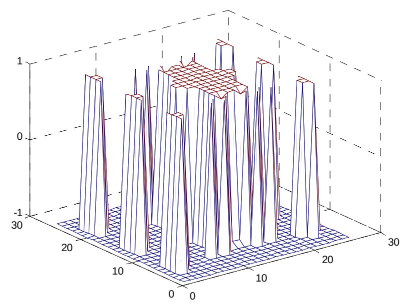
$$\begin{aligned}r'(x,y)\alpha&\left|F\left\{\left|U_j\,(u,v)\right|^2\right\}\right|^2\\ &=\left|\sum C_nC_m^*(r)^n*(r^*)^m\right|^2\end{aligned} \tag{9}$$

Depending on different value for *m* and *n*, Eq. (9) shows different properties. In case of *m=n=1*, the correlation output energy appears similar to the amplitude-only JTC[5] .

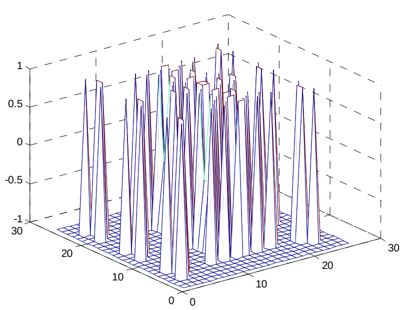
Finally, the proposed optoelectronic recurrent training algorithm for supervised filtering system has been simulated for image feature extraction problems. Initially, 25x25-pixel sized a bipolar image is selected for input and corresponding desired image is selected as a outer corner extracted image. Training algorithm iterates 168 times to converge the desired output. Namely, 168 times cross-correlation has been achieved by POJTC during the training process. Fig. 3 demonstrates the sample of output images for some iteration in the training period.



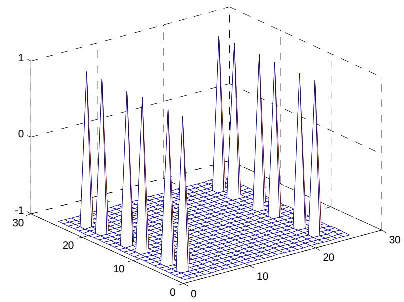
(a)



(b)



(c)



(d)

Fig. 3. Optoelectronic training output for corner detection filtering by SF a) Input images (26x26-pixel) b) Output image of iteration # 80, (c) Output image of iteration # 157, (d) Corner detected output image at iteration # 168.

IV. Conclusion

The proposed optoelectronic training algorithm yields satisfactory performance avoiding high computation burden. POJTC based training algorithm presents significant advantages such as easy hardware application, minimum requirements of optic tools, high speed operation capability. This kind of optoelectronic topology provides availability of combining of training and testing operation in one optoelectronic architecture. In terms of incorporation with other optic applications such as image processing and pattern recognition, the proposed architecture has many advantages compare to digital implementations.

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