An Embedded Lens Controller for Passive Auto-Focusing Camera Device Based on SOM Neural Network

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Abstract- Recently, camera has been widely used in the mobile device in order to provide the function of photograph. In camera’s control techniques, Passive auto-focusing (PAF) has become a tendency to improve the quality of image and the production cost. Basically, the sharpness measurement algorithm is used to measure the focused values of the scene captured. However, the conventional control methods are not very suit for PAF technique due to the full search is still used in PAF control, and it can not efficiently capture the image in a dynamic situation. To decrease the searching time needed, this paper presents a new controller based on SOM neural network. The proposed method is easily to be implemented as the embedded system or be designed as a slimmer and smaller mobile camera device by using a specific integrated circuit. In our study, the implementation is demonstrated by an integrated system which includes CMOS image sensor with adjustable lens, Micro-controller and FPGA.

I. INTRODUCTION

In recent years, the camera function has been asked and set in the mobile devices such as cellular phone, personal digital assistant (PDA) and notebook. Consequently, the high resolution and high quality image is expected to be provided. Generally, the major difference between a digital still camera (DSC) and a mobile device camera is the lens which significantly affects the quality of image taken. As we know, there is no extra place to set the adjustable focused lens in the mobile device since the request of small size. Therefore, the high-pixels but blurred picture is usually the problem of mobile device camera has, even its function is similar to DSC.

In recent studies, PAF algorithm has become a tendency to improve the quality of image. It can be used to measure the sharpness values of image, and then determinate what is the best quality of focused image. The method of comparing with two images captured by different lens’ positions is mainly used in most searching strategies of PAF. However, the best focused values are usually difficult to be determined, especially for different scenes.

In this paper, a new SOM neural network based method which could predict and search the best focused lens position is proposed. Combining with the sharpness measurement approach we proposed, the new developed PAF system is more efficient to reach the best focused lens position. The details of algorithms and hardware implementation are described in the following sections.

II. PASSIVE AUTO-FOCUSING

Basically, the theorem of object captured by camera and the image development is shown in Figure 1. In general, the correct lens position is manually adjusted by the user. For an auto-focusing system, the proper lens position also can be adjusted by an established motor controller based on the measurement by focusing component, such as distance measurement or optical focusing. Passive auto-focusing uses image processing method to estimate the sharpness of picture [1]. A good sharpness measurement algorithm can be used to obtain the higher sharpness value for a clear image than a blurred one. Subsequently, the brief descriptions of sharpness measurement and searching methods will be presented in the following paragraphs.

A. Discrete Wavelet Sharpness Measurement

High frequency signal of image is the sharpness basis for the human vision system. Traditionally, the high-pass filter of image processing is used as the sharpness measurement component. Discrete wavelet transformation (DWT) can be used as the sharpness measurement algorithm [2]. The high-frequency band is taken as the sharpness value. The Lifting 5/3 discrete wavelet transformation is selected and used in this study due to its low complexity and easy implementation for the hardware. In the proposed method, the Lifting 5/3 DWT is designed with the hardware by FPGA.

For Lift 5/3 DWT, the captured two-dimensional image can be transformed by the horizontal and vertical Lifting transformations. Finally, the image can be divided into four bands \{LL, LH, HL, HH\}, where L and H denote the low-band and the high-band, respectively. Due to the sharpness is with respect to high-band signals, the bands LH, HL, and HH of an image can be used to evaluate the
sharpness. Therefore, for an image $P$ with $n$ rows and $m$ columns, the sharpness measurement function $h$ can be calculated by $HH$ band (i.e., the right-bottom quarter of the transformed image). That is,

$$h(P) = \sum_{r} \sum_{c} P_{DWT}(r,c)$$

(1)

where $r$ and $c$ are the row and column indexes of image $P$.

Figure 2 illustrates the DWT results of focused image and blurred image which were transformed by Lifting 5/3 DWT hardware. Obviously, the high-frequency band data in the focused image are clearer than the blurred one. It means DWT can be used for sharpness measurement.

Generally, the ideal curve of sharpness and lens position could be described as Gaussian curve. The practical curves calculated by DWT with different focused images are shown in Figure 3 which illustrates the feasibility of Lifting 5/3 based sharpness measurement.

III. NEW SOM NEURAL NETWORK CONTROLLER FOR BEST FOCUSED LENS POSITION

As mentioned previously, the best focused lens position is not easy to be obtained. The goal of best position searching is to reduce the time of image capturing and fast moving of the lens to the appropriate position without additional steps. In this study, a SOM neural network controller is designed to achieve such a goal.

A. Best Focused Lens Position Searching

At the beginning of PAF procedure, the lens comes back to the start position. Commonly, full search is used to find the best focused position. In this paper, a new search method with prediction technique is proposed as shown in Figure 4. Three samples are measured firstly to predict the best focused position using a specific neural network. After lens moving to the closed position, the lens will come back to search the maximum focused value more exactly.

In Figure 4, the sharpness values of lens positions $s_0$, $s_1$, and $s_2$ are used to predict the candidate of best focused position $s_3$. Then, the best focused position $s_4$ is easily to be obtained. The accurate rate of neural network plays a critical role in prediction step. The detailed SOM neural network method is presented as follows.
B. SOM Neural Network

Self-Organizing Map (SOM) neural network is a well-known unsupervised learning neural network that was introduced by Teuvo Kohonen in year 1982 [3]. The characteristic of SOM neural network is based on competitive learning algorithm. An output neuron won the competition is called a winning neuron. Figure 5 shows a two-dimensional SOM neural network. The input layer and Kohonen layer are defined as vectors $s$ and $k$ respectively, and given by

$$s = [s_1, s_2, ..., s_n]^T \text{ and } k = \left\{ \begin{array}{c} k_{11} \cdots k_{1b} \\ \vdots \ \vdots \\ k_{a1} \cdots k_{ab} \end{array} \right\}$$

(2)

where, $n$ is the length of the input layer (i.e., test data), $a$ and $b$ are the lengths of row and column of Kohonen layer.

Each neuron $k$ of Kohonen layer $k$ has the same dimension as input space $s$. Thus, a weight vectors $w_i$ of $k$ can be expressed as

$$w_i = [w_{i1}, w_{i2}, ..., w_{in}]^T \text{ and } \forall_{i,j}, k_i \in k$$

(3)

where $I$ is the index number of Kohonen layer $k$.

The input vector $s$ (i.e., the test data at lens positions $s_0, s_1,$ and $s_2$ as shown in Figure 4) is fully connected to the array of Kohonen layer $k$ by weight vectors $w_i$. In this paper, $k$ is the training data which was the representative sharpness values of the fixed lens positions $s_0, s_1,$ and $s_2$. Moreover, the initial values of the weight vectors $w_i$ might be selected randomly.

The best-matching neuron of the input vector can be found by minimizing the Euclidean distance between these two vectors. Therefore, the best-matching neuron index (i.e., the winner’s index) of input layer $s$ is denoted as $b(s)$, which is determined by applying the condition,

$$b(s) = \arg \min_i \|s - w_i\|$$

(4)

After the best-matching neuron was found, the weight vectors can be updated. The formula of updating weight vectors can be described as following:

$$w_i(t+1) = w_i(t) + \eta(t)h_i(b_i(t))(s - w_i(t))$$

(5)

where $t$ is discrete time index, $\eta(t)$ is the learning rate, and $h_i(b_i(t))$ is the neighborhood function centered around the winning neuron $b(s)$.

Repeat the training procedure until the training process is terminated. The number of training steps can be fixed prior or stopped when the rate was convergent. Additionally, the trained SOM neural network can be used for predicting the best focused lens position. Once the input data is measured, the data can be input to the trained SOM neural network, and then the output winner neuron will stand the category of the data. According to the category, the controller can move lens to the pre-defined best focused position. The whole proposed PAF procedure is shown in Figure 6.

IV. EXPERIMENTAL RESULTS

In our study, a PAF platform was built; it consists of a CMOS sensor with adjustable lens, a FPGA, and a microprocessor [4]. In this case, the SOM neural network training iteration is set 20. The learning rate $\eta(t)$ is set as 0.97. Beside, the size of the map is set as $5 \times 5$. Figure 7 shows the results of focusing processing of the proposed method. Obviously, this approach is valid for PAF.
V. CONCLUSIONS

This paper presented a new lens control approach which can be applied into PAF system in order to improve the quality of captured image. Unlike the conventional PAF algorithm, the time needed for sharpness measurement and image capturing will be greatly reduced. From the experimental results, the proposed method could use the fewest steps to predict and then move lens to the best focused position. Obviously, the control approach we proposed has shown its potentiality in real commercial applications.

REFERENCES


Figure 7. The proposed PAF Results