Computers and Electronics in Agriculture 145 (2018) 53–62

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Development and implementation of a fish counter by using an embedded system

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ARTICLE INFO

Keywords:
Embedded system
Fish counter
Image processing
Ornamental fish
Raspberry Pi

ABSTRACT

The development and implementation of an instrument for the automatic counting of ornamental fish by using an embedded system, is introduced herein. The proposed instrument is tested with two marine species, the Guppies (Poecilia Reticulata) and Mollies (Poecilia Sphenops), under conditions of controlled lighting and specimens whose sizes vary from 0.5 to 2.3 cm. The counting is done by digital image processing obtaining an average accuracy up to 96.64% using different species of fishes and different sizes. The main contributions are the theoretical and experimental study to determine the aquarium background color and the algorithm of the proposed method implemented in a low cost and high performance embedded system, specifically in a Raspberry Pi 2 executing the free GNU Octave Scientific Programming Language, thus, allowing the counting instrument to be reliable, portable and easily migratory to different operating systems. The obtained results demonstrate that the proposed method is competitive with state-of-the-art ones.

1. Introduction

Fish counting is an open problem in a real environment and it is a priority necessity in aquaculture farming, where the fish count must be performed quickly and reliably for marine species in the process of growth and in some stages of production. On the one hand, knowing the amount of species under cultivation helps to provide the optimum conditions during the cultivation environment, thus guaranteeing the health and growth of the species and the proper inventory of the developed production at the established ranges. Also, the counting process of aquaculture species under cultivation is a complicated problem for some industries, where the characteristics include size, shape, opacity, number of species and environmental conditions in which the cultivation is done, such as: outdoor farm, enclosed space, turbid water, lighting levels and depth of ponds, etc. A traditional technique implemented in aquaculture processes is that from a photograph taken of small quantities of the species, a visual count is performed, thus determining the respecting quantity. However, this manual practice fosters human errors that add uncertainty to the count and is a very slow process. Therefore, a method for counting live fishes in real time is proposed herein. The proposed system is implemented in embedded electronics, which is experimentally tested in a farm named “Brekarand”, a local producer of ornamental fish in northwestern Mexico.

Some studies showing different methods and algorithms for counting fish have been reported in the last three decades. For instance, an automatic fish counting process based on neural networks having an accuracy of 94% to 98% was proposed in (Newbury et al., 1995; Zheng and Zhang, 2010; Fan and Liu, 2013). In (Karplus et al., 2005), a machine for sorting Guppies was proposed, where these were made to go through transparent tubes, moved by a controlled flow and water level. In (Fabic et al., 2013), a method to detect, count and classify fish under water is described. In (Ferrero et al., 2014) two optical low-cost methods are given, the first is based on a set of transmitters and infrared receivers, which detect the presence of a fish when the light beam is divided by the fish silhouette; the second method uses two web cameras, a data acquisition commercial card and a program to process the images developed in LabView™. In (Li et al., 2015) the fishes are counted from an image by using binarization and normed gradients. Other works for counting live fishes are related to computerized vision techniques (Morais et al., 2005; Toh et al., 2009; Labuguen et al., 2012; Loh et al., 2011). A machine vision and image processing for automatic

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https://doi.org/10.1016/j.compag.2017.12.023
Received 3 December 2016; Received in revised form 13 December 2017; Accepted 15 December 2017

classification of the fish type was proposed by utilizing Hu moment invariants (Zion et al., 1999, 2000). In (Zion et al., 2007), two systems were developed for fish classification: the first one uses a background illumination source comprised of eight fluorescent lights, and the second, a monochrome CCD camera installed underwater to capture images. In (Zion et al., 2008) the authors introduced an algorithm to classify and count Guppies (Poecilia reticulata) by gender, using image processing. This work reflects the state of the art and evolution of the last years on the use of computer vision technology in aquaculture (Zion et al., 2012), where a common feature of most works is the use of personal computers, which requires much space, consumes more energy and increases the instrument cost compared to modern embedded systems, like the one introduced in this work.

Embedded systems are quite useful to solve real problems, like Raspberry Pi, which has been applied in (Islam et al., 2014) to implement an electronic voting machine using a camera to take a picture of each citizen who wants to vote. Whether the citizen is valid to vote or not, if has already voted, and allowing the citizen to vote once passed all control filters. Other applications of Raspberry include: house automation (Lamine and Hafedh, 2014; Agrawal and Singal, 2015), image processing to track marine cables (Amir et al., 2014), and monitoring systems (Nguyen et al., 2015; Nikhade, 2015). Raspberry Pi 2 is applied in this work to develop and to implement a low-cost counting system for ornamental fish under the next assumptions: (a) it will have practical application, (b) it will be easy to operate for aquaculture cultivation, (c) it will be cheap, portable and integrated by commercially available components, (d) it will provide counting operation in real time with high levels of reliability, and (e) it will allow technological upgrading.

The proposed system can be feasibly implemented in real environments of farms in two ways:

(i) By placing the digital camera of the fish counter on a fish way that connects two large ponds, where one of the ponds contains the total fishes to be counted, and by forced re-circulation, the fishes will be passed to the other pond. In the counting process, the proposed system will capture images of the fishes from time to time, so that the fishes crossing will be counted in real time. It is worth mentioning that the time of image capture will depend on the speed of the water flow. In addition, in the counting process the proposed system will obtain images of the fishes with a certain time of sampling, so that the fishes crossing will be counted in real time. Notice again that the time of image capture will depend on the speed of the water flow.
(ii) By using a matrix arrangement of the proposed embedded systems strategically placed to cover the entire area of a large aquaculture pond, i.e., each digital camera can cover an evenly distributed subarea, so that each system will function as a separate counter and send the count result to a central coordinating system, which will perform the total count. For this case, an interconnection of systems through a star network topology with Ethernet or Wi-Fi communication, which are integrated in such embedded system, is proposed.

The rest of the article is organized as follows: Section 2 shows the proposed platform and methodology for implementing the counting fish system. Section 3 describes the mathematical foundation, the proposed algorithm, and the mechanical structure. Section 4 provides results and discusses experimental results. Finally, the conclusions are listed in Section 5.

2. Platform and fish counting analysis

The description of an object can be done considering its edges or contours, the shape of the region, or even its texture distribution within such region. According to (Gonzalez and Woods, 2016) there are two ways to address the representation of a region, in terms of its: (a) external characteristics and (b) internal characteristics described by using gray levels. In this work, the proposed fish counting system includes the capture of an image and the distribution of the fish movement in an aquarium. The image is digitally preprocessed to be used within a proposed algorithm to count the fish, and the counting result is displayed on an LCD monitor.

The automatic counting is performed for two fish species from the farm “Brekarand” production, namely: Guppies (Poecilia Reticulata) and Mollies (Poecilia Sphenops). The species are transferred from the culture pond to the container (aquarium). The fish sizes at different stages of growth are in the range of [0.5–2.3] cm, and the quantities of fish submerged in the container have an enormous variation. For the purpose of assessing the accuracy and reliability of the proposed embedded device, the results of around 10,000 images distributed in different stages were processed and analyzed. A Raspberry Pi 2 Model B is used for the fish counting. The system on a chip has 1 GB SDRAM, does not include a hard drive so that to boot and for data storage, a micro SD card is required. The system runs under Linux environment allowing the Quad-Core ARM Cortex-A7 processor run the full range of GNU/Linux, including Snappy Ubuntu Core and Raspbian operating systems. The SD card is resistant to water, temperature, X-rays, magnetism and shock. Finally, the camera of the Raspberry has a resolution of 5 megapixels, manufactured with CMOS technology and fixed focus lens. Its resolution is 2592 × 1944 pixels in images and in video is capable of supporting 1080p30, 720p60 and 640 × 480p60/90. It attaches to the Raspberry by using the dedicated interface CSi designed especially for connecting cameras. Its dimensions are 25 × 20 × 9 mm, and its weigh is 3 g.

2.1. Mathematical analysis for fish counting

The pixels of a digital image can be represented by a matrix A (Gonzalez and Woods, 2016) by Eq. (2.1)

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{a}_{11} & \boldsymbol{a}_{12}\cdots & \boldsymbol{a}_{1n} \\ \vdots & \vdots & \vdots \\ \boldsymbol{a}_{m1} & \boldsymbol{a}_{m2}\cdots & \boldsymbol{a}_{mn} \end{bmatrix}_{\boldsymbol{m}} \times \boldsymbol{n} \tag{2.1}$$

The total pixels of matrix $\boldsymbol{A}$ (2.1) can be estimated by Eq. (2.2)

$$\boldsymbol{N} = \boldsymbol{m} \times \boldsymbol{n} \tag{2.2}$$

The pixels of the digital image represented by matrix $\boldsymbol{A}$ must be within the range of gray levels $[1,2,\ldots,L]$, the number of pixels at level i are denoted by n_i and the total number of pixels by (2.3), where N is the total amount of pixels, and n_i the number of pixels at level i.

$$N = n_1 + n_2 + n_3 + \ldots + n_L \tag{2.3}$$

According to (Huang and Wang, 2009; Gonzalez and Woods, 2016) and in order to simplify the analysis, the gray levels of the histogram regarding them as a probability distribution are normalized by Eq. (2.4),

$$p_i = \frac{n_i}{N},\ p_i \geqslant 0\,,\ \sum_{i=1}^{L} p_i = 1 \tag{2.4}$$

where p_i, is a probability distribution normalized of gray levels, and L is the gray level.

Now, assuming that the pixels are divided into two classes C_0 and C_1 (background and objects, or vice versa) by the k threshold level; C_0 determines pixels with levels $[1,2,\ldots,k]$, and C_1 determines pixels with levels $[k+1,\ldots,L]$. Then, the probabilities of class occurrences are given by Eqs. (2.5) and (2.6), where ω_0 and ω_1 are probabilities of class occurrences.

$$\omega_0 = p_r(C_0) = \sum_{i=1}^{k} p_i = \omega(k), \tag{2.5}$$