Lista de lucrări ştiinţifice relevante

Prof.univ.dr.ing. **GACSÁDI ALEXANDRU**

1. I. Buciu, **A. Gacsádi**, *Directional features for automatic tumor classification of mammogram images,* Biomedical Signal Processing and Control Volume 6, Issue 4, pp.370-378, October 2011.
2. **A. Gacsádi**, P. Szolgay, *Variational Computing Based Segmentation Methods for Medical Imaging by using CNN*, Proceedings of the International Workshop on Cellular Neural Nanoscale and their Applications, Towards Megaprocessor Computing, pp. 418-423, Berkeley, California, USA, February 3-5, 2010.
3. L. Ţepelea, **A. Gacsádi**, I. Gavriluţ, V. Tiponuţ, *A CNN Based Correlation Algorithm to Assist Visually Impaired Persons*, IEEE Proceedings of the International Symposium on Signals Circuits and Systems, pp.169-172, Iasi, Romania, June 30-July 1, 2011.
4. Z. Kincses, Zs. Vörösházi, Z. Nagy, P. Szolgay, T. Laviniu, **A. Gacsádi**, *Investigation of area and speed trade-offs in FPGA implementation of an image correlation algorithm*, Proceedings of the International Workshop on Cellular Nanoscale Networks and their Applications, pp.1-5, Turin, Italy, August 29-31, 2012.
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A CNN Based Correlation Algorithm to Assist Visually Impaired Persons

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Abstract— **This paper presents a correlation algorithm based on the use of cellular neural networks (CNNs) that can improve the features of assisting systems, to give more information from environment to visually impaired persons. The most of operations (calculations) included in the proposed algorithm are achievable by parallel processing. Thus, it can reduce the computing time and the computing time will not increase proportionally with increasing the size of the template images.**

I. INTRODUCTION

There are many people around the world with visual disabilities [1]. According to World Health Report, the number of visually impaired people is over 45 millions.

For these persons mobility is most drastically affected by visual impairment, thereby affecting the movement and work, and as a result of increasing unemployment the rate among these individuals is high (74%) [2][3]. Many efforts have been invested in the last years, based on ingenious devices and information technology, to help people to overcome these barriers and to integrate them in the social and productive life.

Most of systems that assist visually impaired people uses different sensors to detect obstacles, generally in front of the person in a few meters area and communicates the results in different manner: tactile or audio, even through a tactile or audio virtual reality created to give person a spatial information about the environment in which he lives and works [4][5][6][7].

When visually impaired people walks there are a few problems for assisting them: the presence of stairs, up or down, or cavities in the ground and others [5][6]. On the other hand these peoples need important information from environment like: presence of o bus station, the number of bus that arrives, etc. To give that information, we try to include in assisting system an image processing unit in real-time which compare two images, one taken from environment and one from a database. In case of detecting a correspondence between these two images, the system communicates that information to person. Now, for real-time processing of images, we need a supercomputer which costs enormous for these people.

II. TEMPLATE MATCHING OR IMAGE CORRELATION

To analyze the degree of match between two gray-scale images can be used different metrics or procedures such as: Euclidean distance, Sum of Absolute Difference (SAD), Mean Absolute Difference (MAD) and Normalized Cross Correlation (NCC) (eq. 1):

$$\mathrm{Corr}(i,j) = \frac{\sum_{p=1}^{P}\sum_{q=1}^{Q}\left(K(p,q)-\overline{K}\right)\cdot\left(\Lambda(p,q)-\overline{\Lambda}\right)}{\sqrt{\sum_{p=1}^{P}\sum_{q=1}^{Q}\left(K(p,q)-\overline{K}\right)^2}\cdot\sqrt{\sum_{p=1}^{P}\sum_{q=1}^{Q}\left(\Lambda(p,q)-\overline{\Lambda}\right)^2}} \quad (1)$$

where, K(p,q) represents the template image or correlation kernel K: $R^2 \rightarrow R$, and

$\Omega_K=\{(p,q): p\in[1,P], q\in[1,Q], P \text{ and } Q \in R^+\}$

respectively, $\Lambda(p,q)$ represents the current image compared to the template image, Λ: $R^2 \rightarrow R$, and

$\Omega_\Lambda=\{(p,q): p\in[1,P], q\in[1,Q], P \text{ and } Q \in R^+\}$,

$\overline{K}$ is the mean intensity of the template image,

$\overline{\Lambda}$ is the mean intensity of the test image.

The correlation coefficient has the value Corr(i,j)=1 if the two images are absolutely identical, Corr(i,j)=0 if they are completely uncorrelated, and Corr(i,j) = -1 if they are completely anti-correlated, for example, if one image is the negative of the other.

Let us take a gray-scale image $\Phi(m,n)$, where Φ: R2$\rightarrow$R, and $\Omega_\Phi=\{(m,n): m\in[1,M], n\in[1,N], M \text{ and } N \in R+\}$. In the correlation image cases, $\Phi(m,n)$ represent a test image and $\Lambda(p,q)$ represents the current image compared with the template image with central coordinates (i,j).

The test image is scanned pixel-by-pixel so that the template image to completely overlap the test image and the matching degree of each pixel is calculated. The matching degree with the template K(p,q) of a region $\Lambda(p,q)$ from the source image is obtained by computing the correlation coefficient (a numerical index) which indicates how well the pattern matches the contents of that region (compared image). Thus it results the correlation image Corr(i,j) or target image, (figure 1).

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A CNN Implementation of the Horn & Schunck Motion Estimation Method

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Abstract—**In this paper the parallel implementation of the Horn and Schunck motion estimation method in image sequences is presented, by using Cellular Neural Networks (CNN). One of the drawbacks of the classical motion estimation algorithms is the computational time. The goal of the CNN implementation of the Horn & Schunck method is to increase the efficiency of the well-known classical implementation of this method, which is one of the most used algorithms among the motion estimation techniques. The aim is to obtain a smaller computation time and to include such an algorithm in motion compensation algorithms implemented using CNN, in order to obtain homogeneous algorithms for real-time applications in artificial vision or medical imaging.**

Index Terms— **motion estimation, optical flow, cellular neural networks, image processing, real-time applications.**

I. INTRODUCTION

THE data flow, which has to be processed in the case of a sequence of 2D-images, is increased because of the third dimension, namely the temporal one. Motion estimation techniques are estimating the pixels trajectories (motion field) between successive images, in order to express the brightness intensity from current image based on the information from previous or next image. The motion estimation algorithms were developed for different applications such as image sequences analysis, artificial vision or video information compression.

Visual information play a more and more important role in many usual applications which were developed in the last period, based on the technological advance in various fields such as medical imaging, digital and high-definition television, video-conferences, video-telephony, virtual-reality and multimedia techniques. In all these domains, the processing of information obtained from an image sequence is necessary, with the aim to obtain the movement information.

In all applications, motion estimation techniques are estimating the pixel trajectories between successive images in order to express the variation of the brightness intensity from current image based on the information from previous or next image. The resulting information is named "*optical flow*". We have to notice that the optical flow can be different by real movement. In order to obtain an optical flow that represents a good approximation of real movement field, some assumptions or constraints have to be made [1].

II. OVERVIEW ON MOTION ESTIMATION METHODS

The motion estimation methods can be classified in two classes: deterministic methods and probabilistic methods. In the case of probabilistic methods [10,11], the movement is modeled as a random variable. Thus, the ensembles of motion vectors form a random field that is modeled, generally, as a Markov Random Field (MRF). Based on this assumption, it was shown [10] that the joint distribution function, that characterizes the random field, is a Gibbs distribution that is estimated based on a *maximum a posteriori* (MAP) estimator. The probabilistic methods are requiring a very long processing time, but allow modeling the discontinuities in movement field and they are not limited to certain movement models. The study of probabilistic methods will be the subject of a next research project.

In practice, the deterministic methods are used, the processing time being much smaller. Between the deterministic methods, the most used are [1,2,11]:

- differential methods (or gradient methods), in this case the motion being estimated based on the spatial and temporal gradients of images;

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A CNN PATH PLANNING FOR A MOBILE ROBOT IN AN ENVIRONMENT WITH OBSTACLES

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In this paper a method for visual control based on images of a mobile robot in an environment with obstacles is proposed. Cellular Neural Networks are used here for path planning of a mobile robot, in real time.

1 Introduction

An important issue that can be found in robotics is the path planning for a mobile robot in an environment with obstacles, where the trajectory starts from an initial point in the workspace and it ends at the desired position called target. There are several solutions for this issue. These solutions are determined using, very often, one of the following methods [3,4]:

a) Path planning or robot navigation using a global method.

The global method is related with the superior hierarchical level in the robot control theory. Using this method, the optimal trajectory is obtained by avoiding the static and moving objects, known in the workspace. The global methods are often based on mapping the environment and they approach the problem only from a geometrical point of view.

b) Path planning or robot navigation using local methods.

The local method could be related to the inferior hierarchical level in the robot control theory. In this case the robot control could be obtained using the prescribed trajectory determined through a global path planning method. Using local methods, unknown static or moving obstacles are avoided, compensating the uncertainty of data sets given by the global method. Local planning or navigation takes into account, the kinematics and also the dynamics of a robot, because this planning is based on the information obtained from signals, which can be processed in real time. But, using only local information the optimal solution for the prescribed trajectory is not guaranteed and it cannot be started if the target is reached. These two approaches are often used together, namely the global planning is used for achieving a possible trajectory and local navigation is used for local optimization of the trajectory and for avoiding unexpected obstacles. For local navigation, "graph" methods or "fields of potential" methods can be used.

Cellular neural networks (CNN) can be successfully used in a wide spectrum of applications, starting with modeling of biological phenomena, image processing, navigation a mobile robot, etc., [1,2,5,6]. The environment with obstacles is put into a discrete image and this way it is possible to represent the workspace through a standard network having M*N cells. The values of pixels for gray-scale images are in the interval [-1,1], known as the standard domain in CNN. For binary images, these values could be only +1, for the black pixels and −1 for white pixels.

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Directional features for automatic tumor classification of mammogram images☆

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A B S T R A C T

One way for breast cancer diagnosis is provided by taking radiographic (X-ray) images (termed mammograms) for suspect patients, images further used by physicians to identify potential abnormal areas thorough visual inspection. When digital mammograms are available, computer-aided based diagnostic may help the physician in having a more accurate decision. This implies automatic abnormal areas detection using segmentation, followed by tumor classification. This work aims at describing an approach to deal with the classification of digital mammograms. Patches around tumors are manually extracted to segment the abnormal areas from the remaining of the image, considered as background. The mammogram images are filtered using Gabor wavelets and directional features are extracted at different orientation and frequencies. Principal Component Analysis is employed to reduce the dimension of filtered and unfiltered high-dimensional data. Proximal Support Vector Machines are used to final classify the data. Superior mammogram image classification performance is attained when Gabor features are extracted instead of using original mammogram images. The robustness of Gabor features for digital mammogram images distorted by Poisson noise with different intensity levels is also addressed.

1. Introduction

Image manipulation is commonly used in image processing and pattern recognition field. Image manipulation may include quality enhancement, filtering, segmentation, feature selection or extraction and dimensionality reduction, to mention only a few. When it comes to image classification, it is desirable to keep discriminant features and discard non-relevant features that may negatively affects the classification performances.

Mammographic images are X-ray images of breast region displaying points with high intensities density that are suspected of being potential tumors. Early diagnostic and screening is crucial for having a successful medical treatment or cure. Typically, masses and calcium deposits are easily identified by visual inspection. These deposits appear much denser (highly attenuate X-ray) than others types of surrounding soft tissues. Malign tumors are usually associated to unusual smaller and clustered calcification. Other calcification types, including diffuse, regional, segmental or linear, correspond to benign tumors. Such calcification are termed as microcalcification. Automatic tumor classification would require the segmentation of the microcalcification area from the X-ray image, followed by recognition or classification of the segmented area into one of theses three classes: normal tissue (absence of tumor), benign or malign tumor. Automatic tumor detection is extremely challenging as the suspicious calcification or masses appear as free shape and irregular texture, so that no precise patterns can be associated to them. In addition, the presence of more or less prominent blood vessels and muscle fibers may seriously degrade the accuracy of identification or tumor recognition.

Several techniques have been proposed to analyze, detect or to extract features from mammogram images. Strickland and Hahn [1] proposes a two-stage method based on wavelet transforms for detecting and segment calcifications. In the first stage the image is decomposed into four sub-bands ((LL, LH, LH, and HH) without downsampling. Detection is next performed for the HH sub-band and the combination of LH+HL. Four octaves are computed with two inter-octave voices for finer scale resolution. The second stage improves the accuracy of segmentation, where detected pixel sites in HH and LH+HL are dilated and weighted before taking the inverse of the wavelet transform. By so doing, the microcalcifications are greatly enhanced in the resulting image and an appropriate threshold can be used to segment the tumor zone. Haar wavelets along with PCA are proposed by Swiniarski et al. [2] to extract relevant features, and rough sets methods are further employed to classify the resulting features. Recently, the authors extended the work by extracting independent component features, followed by rough sets method for feature selection and data reduction, and, ultimately, a rule-based classifier is employed for a final decision

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IMAGE INPAINTING METHODS BY USING CELLULAR NEURAL NETWORKS

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ABSTRACT

Some CNN methods are presented that can be used for the reconstruction of damaged or partially known images. The proposed methods take the possibility of direct implementation on an existing CNN chip into account, in a single step, by using 3*3 dimensional linear reaction templates. Due to complete parallel processing, computational time reduction is achieved. Efficiency of these methods can be increased by combining them with nonlinear template that ensures the growth of the local properties spreading area along with regional ones.

1. INTRODUCTION

Image inpainting is an interpolation problem where an image with missing or damaged parts is restored. An observer not familiar with original image, practically will not notice that the image has been restored. The most often used image inpainting applications are for pictures or films known or damaged partially. In image restoration it is possible to obtain special effects, eliminating some unwanted parts, texts or objects [5][6][7].

As a first step the user manually selects the portions of the image that will be restored. Then image restoration is done automatically, by filling these regions in with information coming from the surroundings. The output image is of the same dimensions and resolution as the input image [8][10].

In the case of image restoration, the unknown parts may be bigger, and they generally do not contain any information, while in the case of denoising, the pixels contain information with additive noise [9][14].

Complex mathematical models based on partial differential equations (PDE) are available in the field of reconstruction or inpainting of damaged image [4].

Let us take a gray-scale image $\Phi(x,y)$ where Φ: $\mathbf{R}^2 \rightarrow \mathbf{R}$, and $\mathbf{\Omega}=\{(x,y): x\in[1,M], y\in[1,N], M \text{ and } N \in \mathbf{R}^+\}$. The processing of this image, with an algorithm based on an operator, can be described by the following partial differential equation:

$$\frac{\partial\Phi}{\partial t} = F\left[\Phi(x,y,t)\right], \tag{1}$$

where an artificial parameter t has been used and F is the operator which characterizes the desired processing algorithm (F: $\mathbf{R}^2 \rightarrow \mathbf{R}$). In general, function F depends on the initial image, and its first and second order spatial derivatives. The final image is a solution of this partial differential equation. By using a variational formulation, the same image processing problem can be obtained as the minimization of a cost function:

$$\arg\{\mathrm{Min}_{\Phi} E(\Phi)\}, \tag{2}$$

where E is a given energy function, and F is the first order derivative of E. Through minimizing E, Φ results from the condition: $F(\Phi)=0$, which is a steady state solution of equation:

$$\frac{\partial\Phi}{\partial t} = F(\Phi), \tag{3}$$

where t is also an artificially introduced parameter.

Regardless of the chosen formulation for modeling the image processing, two or more obtained solutions allow us to make combinations of them, resulting in another complex processing. If, e. g., two distinct processing are described by cost functions E_1 and E_2, another complex image processing can be formulated minimizing the energy:

$$\alpha E_1 + \lambda E_2 . \tag{4}$$

Weighting the terms E_1 and E_2, with scalar parameters α and λ (α and $\lambda \in \mathbf{R}^+$), let us balance the complex processing between the limits described by the initial results.

Considerable computing power is necessary to solve the image processing task described by variational computing. For the time being serial processing does not provide us with methods implementable in real-time. The Cellular Neural Networks proved to be very useful regarding real-time image processing [1]. The reduction of computing time, due to parallel processing, can be obtained only if the processing algorithm can be implemented on a CNN-UC [3].

Even if variational methods are used, the determination of templates ensuring the gray-scale image the desired processing remains a difficult problem, since the fact that the actually existing CNN chip can use only linear templates having 3*3 dimension has to be taken into consideration. In some cases templates satisfy these conditions [11] by using nonlinear templates. Effective CNN implementation is still possible in CNN algorithms [13].

Investigation of area and speed trade-offs in FPGA implementation of an image correlation algorithm

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Abstract—In this paper an image correlation algorithm is implemented on FPGA architecture for assisted movements of visually impaired persons or automotive driving systems. Taking into account the limitations of FPGA devices and the special requirements of the correlation based image matching algorithm a semi-parallel approach is proposed. This provides an optimal trade-off between area and speed of the implemented algorithm. Several key issues are investigated and discussed related to the speed and area.

I. Introduction

In general, determination of a correlation coefficient between two images requires high computing power, which is proportional to the size of the template image (kernel). It is desirable that the template image size should be large enough to contain relevant information. For real-time computation of the correlation coefficients, the majority of the operations can be executed on a CNN algorithm as described in [1]. However, analog CNN VLSI implementations have relatively low precision (7-8 bits) and very sensitive to the small changes of temperature and supply voltage. For these reasons an FPGA-based implementation is chosen.

II. Image Correlation: Mathematical Backgrounds

Similarity matching between two gray-scale images can be classified into feature-based and intensity based-methods. In case of the intensity based methods different metrics or procedures can be applied, such as: Euclidean distance, Sum of Absolute Differences (SAD), Mean Absolute Differences (MAD), Sum of Squared Differences (SSD) or Normalized Cross Correlation (NCC) [2].

The NCC in equation (1) can be easily derived from the SSD: maximizing the correlation is equivalent to minimizing the sum of squared differences, which effectively gives more weight to large differences. Let us consider an input test image $\Phi(m,n)$: $R^2 \rightarrow R$ with dimension M×N. Correlation values can be computed as follows [1]:

$$\boldsymbol{CORR(i,j)} = \frac{\sum_{p=1}^{P}\sum_{q=1}^{Q}\left[\boldsymbol{K(p,q)}-\overline{\boldsymbol{K}}\right]\cdot\left[\Lambda(\boldsymbol{p,q})-\overline{\Lambda}\right]}{\sqrt{\sum_{p=1}^{P}\sum_{q=1}^{Q}\left[\boldsymbol{K(p,q)}-\overline{\boldsymbol{K}}\right]^2}\cdot\sqrt{\sum_{p=1}^{P}\sum_{q=1}^{Q}\left[\Lambda(\boldsymbol{p,q})-\overline{\Lambda}\right]^2}} \quad (1)$$

where $K(p,q)$: $R^2 \rightarrow R$ denotes the template image (correlation kernel) with dimension P×Q ($p \in [1,P]$, $q \in [1,Q]$),

$\Lambda(p,q)$: $R^2 \rightarrow R$ represents the actual image region from test image $\Phi(m,n)$ compared to the kernel $K(p,q)$, with dimension P×Q, ($p \in [1,P]$, $q \in [1,Q]$), respectively.

$\overline{\boldsymbol{K}}$: is the mean intensity value of the template image

$\overline{\boldsymbol{\Lambda}}$: is the mean intensity value of the test image.

The gray-scale input test image is scanned pixel-by-pixel and overlapped with a kernel as a sliding window to calculate the matching degree for each pixel (i,j) as can be seen in Figure 1. The matching degree between the template $K(p,q)$ and an actual image region $\Lambda(p,q)$ from the test image $\Phi(m,n)$ is obtained by computing the square of correlation coefficient ($CORR^2(i,j)$), which indicates how well the pattern matches the contents of that region (compared image). Equation (1) can be rewritten as follows:

$$\boldsymbol{CORR}^2\boldsymbol{(i,j)} = \frac{\left\{\overline{\left[\boldsymbol{K(p,q)}-\overline{\boldsymbol{K}}\right]\cdot\left[\Lambda(\boldsymbol{p,q})-\overline{\Lambda}\right]}\right\}^2}{\overline{\left[\boldsymbol{K(p,q)}-\overline{\boldsymbol{K}}\right]^2}\cdot\overline{\left[\Lambda(\boldsymbol{p,q})-\overline{\Lambda}\right]^2}} \quad (2)$$

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Medical Image Enhancement by using Cellular Neural Networks

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Abstract

The paper presents a medical image enhancement method taking the noise reduction and the contrast enhancement into consideration, as well as the possibility of implementation on an existing cellular neural network universal chip (CNN-UC), in a single step, by using only linear templates of 3×3 dimensions. Due to complete parallel processing, computing-time reduction is achieved.

1. Introduction

The problem of medical image enhancement, became more and more important in the last decade. Another challenging in medical imaging is to obtain real-time applications. In this paper we propose a fully-parallel solution to achieve the medical image enhancement.

The method, based on Cellular Neural Networks (CNN) [1], is suitable for real-time processing.

Cellular Neural Networks (CNN) [1], CNN-Universal Machine's (CNN-UM) [2] architecture and CNN Universal-Chip (CNN-UC) [3] has proved to be a competing alternative to classical computational techniques. A Cellular Neural Network is a 2-dimensional rectangular structure, composed by identical analogical non-linear processors, named cells [2]. The CNN allows fully-parallel image processing, a given processing being executed simultaneously for the entire image.

The state equation of a cell is [1]:

$$\dot{x} = \frac{dx_{ij}}{dt} = -x_{ij} + \sum_{C_{lk} \in N_r} A_{ij,lk} \cdot y_{lk} + \sum_{C_{lk} \in N_r} B_{ij,lk} \cdot u_{lk} + z_{ij} \quad (1)$$

where x_{ij} represent the state, u_{ij} is the input, y_{ij} is the output and z_{ij} is the threshold of the cell (i,j). $A_{ij,kl}$ is the feed-back operator and $B_{ij,kl}$ is the input operator. The ensemble (A, B, z) is named template. C_{lk} are the cells from a r-order neighborhood N_r of the cell (i,j):

$$N_r(i,j) = \left\{ C(l,k) \middle| max\left\{ |l-i|, |k-j| \right\} \le r \right\} \quad (2)$$

with $1 \le i,l \le L$, $1 \le j,k \le K$, $r \le \min(L,K)$. K and L are the dimensions of the network.

The structure of a cell C_{ij} is presented in Figure 1:

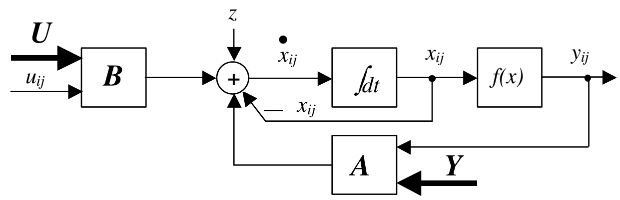

Figure 1. System structure of a cell C_{ij}.

In Figure 2, the signal flow structure of a CNN with a 3×3 neighborhood [2].

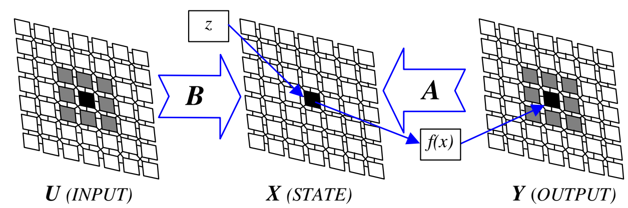

Figure 2. Signal flow structure of a CNN with a 3×3 neighborhood.

2. PDE image processing

Generally, the image processing tasks could be described by a PDE (Partial Differential Equation). Whatever the image processing described by a PDE is, a considerable computing power is necessary. Regarding this problem, the Cellular Neural Networks (CNN [1]) proved to be very helpful regarding the real-time image processing, as well as solving some partial differential equations [4,5]. Reduction in computing time due to parallel processing, can be obtained only if the processing algorithm can be implemented on a Cellular Neural Networks-Universal Chip (CNN-UC [3]), having the architecture of a Cellular Neural Networks-Universal Machine (CNN-UM [2]).

Recently, the interest in using partial differential equations (PDE-s) has grown in the field of image processing and analysis [6,10]. Let us consider a gray-scale image $\Phi_0(x,y)$, Φ_0: $\mathbf{R}^2 \rightarrow \mathbf{R}$. The processing of this image, according to an algorithm based on an operator, can be described by the following partial differential equation:

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Motion Planning for Two Mobile Robots in an Environment with Obstacles by Using Cellular Neural Networks

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Abstract **- The paper presents a visual control algorithm based on images, for two mobile robots in an environment with obstacles. Cellular Neural Networks (CNNs) processing techniques are used here for motion planning in real time of two mobile robots moving to the same target. The algorithm can be extended for three or more robots.**

I. INTRODUCTION

A challenge in autonomous robotics is the navigation in unstructured environments using vision-based algorithms. These algorithms should guide one or more robots from an initial position to a target position, avoiding obstacles located between these positions. If we take into account that the obstacles as well as the target can move and that the obstacles can have any shape, it becomes clear that this problem is not a trivial one.

There are several solutions to solve this problem, each of them being included in the global or/and local control method of robot. The global method for path planning or robot navigation is related with the superior hierarchical level in the robot control theory. On the other hand, the local method could be related with the inferior hierarchical level in the robot control theory. These two approaches are often used together, namely the global planning is used for achieving a possible trajectory avoiding obstacles, while local navigation is used for local optimization of the path and for avoiding unexpected obstacles [6,7,9].

Cellular neural networks (CNN) can be successfully used in a wide spectrum of applications [1,2]. The CNN methods have been considered as a solution for images processing in mobile robots guidance. The choice of CNNs for the visual processing part lies on the possibility of their hardware implementation in large networks on a single VLSI chip. A variety of approaches have been proposed to use CNNs for a single mobile robot path planning which is moving in unstructured environments [5,8,11].

Usually the environment with obstacles is divided into discrete images and in this way it is possible to represent the workspace in the form of an M*N array, through a standard neural network having M*N cells. The processed images are gray-scale, having the value of the pixel in the interval [-1,1], known as the standard domain in CNN. For binary images, these values could be only +1 for the black pixels and –1 for white pixels

This paper is organized as follows: In Section II we briefly review the cooperation between mobile robots. In Section III a CNN algorithm for the guidance of two mobile robots is presented. Simulation results are shown in Section IV. Some conclusions and future directions of the research are given in Section V.

II. COOPERATION IN MOBILE ROBOTS SYSTEMS

Research in autonomous robots has recently taken a new approach, namely, the multi-robot approach, in which systems are designed, that distribute to varying degrees, actuation and sensing to perform tasks with or without some form of cooperation. Examples requiring distributed actuation include: floor washing, lawn moving, vacuuming, crop harvesting or wall cleaning, all possible by one robot, without cooperation, given enough time. On the other hand there are the cooperative tasks, requiring more than one robot; examples include heavy object transportation, fluid containment or fire control. Distributed sensing tasks require the system to perceptually cover an area spatially and might include such tasks as mine sweeping, mapping, searching or environmental monitoring. Both cooperative and non-cooperative forms of these tasks exist, and can be differentiated by imposed constraints such as whether a fixed formation needs to be maintained [3,4].

Designing systems for these tasks requires architectural decisions to be made. Architectures make use of either a heterogeneous or a homogeneous set of robots. Explicit communication between robots varies from none to a fully connected topology, where each robot has access to full global knowledge. System size ranges from a few robots to more than 100, with most systems reporting experimental results with physical implementations having less than 10 robots.

Tasks used in the study of multi-robot control include foraging, which involves searching and retrieving items from a given area; box-pushing, which moves an object between two

PDE-Based Medical Images Denoising Using Cellular Neural Networks

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***Abstract* — This paper presents the medical image denoising by using Cellular Neural Networks (CNN), based on the variational model of Chan and Esedoglu [1]. There are also comparatively analyzed the proposed method and other CNN methods that uses variational computation, our proposed method offering the best efficiency in terms of image denoising and edge preservation.**

I. Introduction

Nowadays, the investigative techniques such as Magnetic Resonance Imaging (MRI) Computer Tomography (CT) or Positron Emission Tomography (PET), play an important role in medicine. In order to extract as much information as possible, these techniques are using advanced methods of image processing. So, 3D techniques can be used to make better visualization, feature extraction can be used for assisted diagnostics, segmentation can be used to separate the different tissue parts and image denoising methods can be used to improve the image quality. In order to make a proper visualization, the different body parts need to be segmented and in order to make a good segmentation, noise needs to be removed.

Finding new efficient image denoising methods is still a challenge in many research fields. Despite many sophisticated recently proposed methods, most of the algorithms didn't reach the desired applicability level especially because of the high computational time. The majority of these methods prove remarkable performances when the processed image corresponds to the model of the algorithm, but contrary fails or gives significant artifacts.

The performances of the image denoising techniques are difficult to be evaluated. They can be compared using some experimental quantitative measures, but the best evaluation method seems to be the visualization of the effects on natural images [2].

In fact the denoising is the recovery of an original image Φ_0, from the noisy input Φ. Homogeneous regions separated by edges must compose the recovered image. Two phenomena cause image damaging: one is linked to the acquisition method (for instance the acquisition of CT images from projections, or the blurring caused by movement); the other one is caused by random noise that is associated with any signal. In the field of medical imaging, the additive Gaussian white noise represents a significant weight and therefore we will treat this kind of noise [2].

The simplest image model that takes the noise into consideration is the linear degradation model:

$$\Phi = \Phi_0 + \eta , \qquad (1)$$

where Φ_0 is the original image, Φ is the observed and damaged image, η represents the random additive noise. Image restoration can be interpreted this way as a reverse problem.

There are several methods for removing Gaussian noise from medical images including complex mathematical models based on partial differential equations (PDE) [3,4,5,6]. In order to solve these equations, regularization methods could be used. The regularization method constitutes an interesting alternative to the nonlinear diffusion method [7,8].

II. PDE Based Medical Images Denoising

Let us take a gray-scale image $\Phi(x,y)$ where Φ: $R^2 \rightarrow R$, and $\Omega=\{(x,y): x\in[1,M], y\in[1,N], M \text{ and } N \in R^+\}$. The processing of this image, with an algorithm based on an operator, can be described by the following partial differential equation:

$$\frac{\partial \Phi}{\partial t} = F\left[\Phi(x,y,t)\right], \qquad (2)$$

where an artificial parameter t has been used and F is the operator which characterizes the desired processing algorithm (F: $R^2 \rightarrow R$). In general, function F depends on the initial image, and its first and second order spatial derivatives. The final image is a solution of this partial differential equation. By using a variational formulation, the same image processing problem can be obtained as the minimization of a cost function:

$$\arg\{\mathrm{Min}_{\Phi} E(\Phi)\}, \qquad (3)$$

where E is a given energy function, and F is the first order derivative of E. Through minimizing E, Φ results from the condition: $F(\Phi)=0$, which is a steady state solution of the equation:

$$\frac{\partial \Phi}{\partial \mathrm{t}} = F(\Phi), \qquad (4)$$

where t is also an artificially introduced parameter.

An example for the equivalence of the variational method with the PDE method is Dirichlet's integral:

$$E(\Phi) = \int |\nabla\Phi|^2 (\mathrm{x}) \mathrm{dx}, \qquad (5)$$

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Variational Computing Based Segmentation Methods for Medical Imaging by using CNN

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Abstract—**The paper presents a new variational computing based medical image segmentation method by using Cellular Neural Networks (CNN). By implementing the proposed algorithm on FPGA (Field Programmable Gate Array) with an emulated digital CNN-UM (CNN-Universal Machine) there is the possibility to meet the requirements for medical image segmentation.**

Keywords-medical imaging; segmentation; variational computing; cellular neural networks;

I. INTRODUCTION

Segmentation of images by defining anatomical structures and regions of interest have a crucial role in most medical imaging applications, both in the phase of establishing the diagnosis by locating pathology, and in planning and carrying out appropriate treatment, such as for example, biopsy, radiation therapy, and minimally invasive surgery. In this respect automatic segmentation is a set of methods to create using relevant images the specific anatomical model of the patient. A typical situation for semiautomatic systems for aided diagnosis involving labeling occurs when the image is segmented into different regions and regions are subsequently labeled as healthy tissue or a tumor. For this purpose may be used, for example, Magnetic Resonance Imaging (MRI), Computer Tomography (CT) or Positron Emission Tomography (PET).

A variety of approaches have been developed to solve the problem of images segmentation which is an important stage in an automatic diagnosis system. First, for grey scale images, one may classify the segmentation methods into edge-based methods and region-based techniques. Region-growing methods can be made less sensitive to noise than simple edge-based or morphological methods, but they may become extremely computationally complex for even simple rules. On the other hand, curve evolution, active surfaces, statistical approaches, and variational energy methods have become popular approaches in this field. The majority of these methods prove remarkable performances when the processed image corresponds to the model of the algorithm but fails or gives significant artifacts otherwise [1].

The process used to perform image segmentation varies greatly depending on specific application, imaging modality and other factors. In practical terms it seems that a model should be selected according to its specific application. The optimal method of processing may depend on how was the input image generated namely, it is a CT or a MRI image. Moreover, in CT images brain tissue segmentation has different requirements from the segmentation of the liver. Overall image artifacts such as noise and movement can also have significant consequences on the choice of appropriate segmentation algorithm. In addition, each imaging modality introduces its own difficulties, which hinder the election and execution of the optimal segmentation method.

The performances of segmentation techniques are difficult to evaluate. Currently there isn't a specific general method of segmentation to produce acceptable results for all types of medical images. Each of these methods have their advantages and disadvantages, as some algorithms optimized for a particular hardware structure can no longer work as well on another structure. However, some methods available for relatively large areas, which are optimized for specific applications, can often produce better results by taking into account previous knowledge. Therefore, selecting an optimal segmentation method for a concrete application can be a difficult issue, being a continuous dilemma, and by far it is not a classic algorithm and a classical filtering application, e.g. min/max algorithm.

Mathematical models are the foundation of biomedical computing [2]. Based on those models data extracted from images continues to be a fundamental technique for achieving scientific progress in biomedical research. It is extremely important to notice that regardless of the mathematical algorithm used for segmentation and the method of implementation, assessing in whole their efficiency and utility, that is validating the algorithm for daily medical practice, results from an iterative loop process, where the radiologists play very important role. However, there is a major need for new mathematical techniques and possibilities of implementation that will lead to more efficient methods that can be integrated into the semiautomatic systems [2]. Certainly

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