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Segmentation of Rumex Obtusifolius Using Simple Fuzzy Logic and Gmrf

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ABSTRACT
Rumex obtusifolius is a common weed that is difficult to control. In general, weed control is done by using herbicides because of its adverse environmental impact, Robotic systems are considered as a suitable non-chemical alternative for removing Obtusifolius. Among the existing systems of weed control, only few are applicable to real time applications of weed control. Here we develop a new algorithm for segmentation of rumex obtusifolius. The new algorithm is based on Fuzzy logic and GMRF property that is used for the detection of the weed. *Fuzzy logic and markov random fields that works in real time under natural lighting conditions. We also show its performance by comparing it with the existing real time algorithm that uses only markov random fields. This is not only suitable for the detection of the weeds, but also suitable for various general applications like in the detection of the tumors in MRI scanned images, detection of object in an image etc.*

Keywords: Rumex obtusifolius, GMRF texture, Segmentation, Fuzzy logic.

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I. INTRODUCTION

Rumex obtusifolius is a general weed identified in the Netherlands. The major concern about this weed is it competes with grass for natural resources like water, nutrients, and light for its growth thereby reducing crop yield. One of the widely used methods of controlling weeds is by application of herbicides; however, the use of herbicides is being questioned due to their adverse affects on the environment. For instance, herbicides are found to cause ground water pollution and force selective bias towards herbicide-resistant weeds. There are present several non-chemical methods for controlling weeds, like crop rotation, manual removal, thermal and biological control. However these methods are labor intensive, non-scalable, and expensive both in time and costs. As a result, for mechanical treatment of weed robotic systems are being considered. The systems [4] go for vision-based methods for detection of the weed. Our focus is on detection of R.Obtusifolius in grasslands. Most of the available vision-based robotic systems for detecting weeds are not suitable for real-time detection of R. obtusifolius in grasslands for several reasons. We can observe that many methods focus on detection in soil background using color contrast between soil and weed. These methods are not suitable to be applied for detecting R. obtusifolius in grassland because they are characterized with similar spectral reflectance in visible range. Another [7] method that uses uniformity-based texture measure to detect weeds in lawn field is available. This technique is not adaptable in grasslands, because unlike in a lawn, the grass does not have a consistent texture. In local variance was used as the texture measure to detect broad-leaf weeds in grassland. Local variance is another measure of uniformity of texture, and our preliminary analysis showed that it is unreliable because of the inconsistency of grass texture. A real-time vision system which uses spectral power as a texture measure was developed in for the detection of R. obtusifolius in grassland. In this method, the image is partitioned in to square tiles. Each tile is classified based on its spectral power either as weed or grass. They report satisfactory performance; however, they also mention that it is sensitive to illumination condition. Local spectral power and local variance are same in nature thus suffers from the same drawbacks as mentioned above. The authors have exploited the difference in density of edges between grass and weed regions and developed a texture measure based on edge strength. The veins and ribs of R. obtusifolius form strong edges due to which differentiating it from grass based on edge strength alone is difficult. In the study of detecting weed in lawn field, the authors use texture features[8] based on Grey-level co-occurrence matrix (GLCM).

GLCM features are one of the most widely used texture features, but cannot be applied in real time because they are computationally expensive.
The aim of this study is to develop a robust, vision-based, real-time segmentation method for detection of R.obtusifolius in grassland under natural lighting conditions. Segmentation of R. obtusifolius in grassland entails uncertainty in terms of shape, size and illumination. Figure 1 shows a typical image of R.obtusifolius in grassland taken by the robot. Here we can see, not only the spatial (spectral and textural) properties of grass and Rumex pixels vary but also the spatial properties of grass pixels in different parts of the mage. Further, this pattern varies from image

Fig. 1 A typical image of R. obtusifolius

To image. A robust segmentation algorithm should account for these uncertainties. The one such type of robust method is by using only GMRF (Gaussian Markov Random Fields). But this method cannot detect the rumex accurately and so to overcome this drawback here we propose a new method. The new algorithm is based on Fuzzy logic and GMRF property that is used for the detection of the weed. Markov random field (MRF) theory helps us to deal with uncertainties in an image by means of explicitly defining the spatial context and describing the spatial interactions between pixels as a probability distribution. The suitability of MRFs for modeling natural images has been demonstrated in several studies. We assume that the image has only two classes, Rumex and grass and model it as a Gaussian MRF (GMRF). GMRF is one of the simplest MRF that is suitable for encoding spatial interactions between pixels and can be easily estimated using Least squares. The term "fuzzy logic" was introduced with the proposal of fuzzy set theory by Lotfi A. zadeh. Fuzzy logic has number of applications, from control theory to artificial intelligence. Here Fuzzy logic uses Edge detection method to find the weed edge pixels, by applying the rules to each pixel along with its 8-neighbourhood [2]. Before applying the rules, each pixel is categorized into a "white" and "black" pixel using the triangular membership function. The rest of paper is organized as follows. Section 2 gives basic definitions and notations of MRF theory. Sect 3 describes about GMRF. The fuzzy logic with edge detection is described in Sects.4. The Image model is represented in sect 5. The performance comparison for existing and proposed methods are discussed in Sect.6 followed with conclusion.

II. MARKOV RANDOM FIELDS

Given an undirected graph $G = (V, E)$, a set of random variables $X = (X_v)_{v \in V}$ indexed by V form a Markov random field with respect to G if they satisfy the local Markov properties:

2.1 Properties of the MRF:

1. Pair wise Markov property: Any two non-adjacent variables are conditionally independent given all other variables:

$$X_u \perp\!\!\!\perp X_v \mid X_{V \setminus \{u,v\}} \quad \text{if } \{u,v\} \notin E$$

2. Local Markov property: A variable is conditionally independent of all other variables given its neighbors:

$$X_v \perp\!\!\!\perp X_{V \setminus \mathrm{cl}(v)} \mid X_{\mathrm{ne}(v)}$$

Where ne(v) is the set of neighbors of v, and cl(v) = {v} ∪ ne(v) is the closed neighborhood of v.

3. Global Markov property: Any two subsets of variables are conditionally independent given a separating subset:

$$X_A \perp\!\!\!\perp X_B \mid X_S$$

Where every path from a node in A to a node in B passes through S.
The above three Markov properties are not equivalent to each other at all. In fact, the Local Markov property is stronger than the Pair wise one, while weaker than the Global one.

2.2 Clique factorization:

As the Markov properties of an arbitrary probability distribution can be difficult to establish, a commonly used class of Markov random fields are those that can be factorized according to the cliques of the graph. Given a set of random variables $X = (X_v)_{v \in V}$, let $P(X = x)$ be the probability of a particular field configuration x in X. That is, $P(X = x)$ is the probability of finding that the random variables X take on the particular value x. Because X is a set, the probability of x should be understood to be taken with respect to a product measure, and can thus be called a joint density.
If this joint density can be factorized over the cliques of G:

$$P(X = x) = \prod_{C \in \mathrm{cl}(G)} \phi_C(x_C)$$

then X forms a Markov random field with respect to G. Here, cl(G) is the set of cliques of G. The definition is equivalent if only maximal cliques are used. The functions φ_C are sometimes referred to as factor potentials or clique potentials. Note, however, conflicting terminology is in use: the word potential is often applied to the logarithm of φ_C. This is because, in statistical mechanics, $\log(\varphi_C)$ has a direct interpretation as the potential energy of a configuration x_C.

Although some MRFs do not factorize a simple example can be constructed on a cycle of 4 nodes in certain cases they can be shown to be equivalent conditions:

If the density is positive by the Hamersley–Clifford theorem, if the graph is chordal by equivalence to a Bayesian network.

When such a factorization does exist, it is possible to construct a factor graph for the network.

2.2.1 Logistic model:

Any Markov random field (with a strictly positive density) can be written as log-linear model with feature functions f_k such that the full-joint distribution can be written as

$$P(X=x)=\frac{1}{Z}\exp\left(\sum_k w_k^\top f_k(x_{\{k\}})\right)$$

Where the notation is as follows

$$w_k^\top f_k(x_{\{k\}})=\sum_{i=1}^{N_k} w_{k,i}\cdot f_{k,i}(x_{\{k\}})$$

Is simply a dot product over field configurations, and Z is the partition function:

$$Z=\sum_{x\in\mathcal{X}}\exp\left(\sum_k w_k^\top f_k(x_{\{k\}})\right).$$

Here, $\mathcal{X}$ denotes the set of all possible assignments of values to all the network's random variables. Usually, the feature functions $f_{k,i}$ are defined such that they are indicators of the clique's configuration, i.e. $f_{k,i}(x_{\{k\}})=1$ if $x_{\{k\}}$ corre sponds to the i-th possible configuration of the k-th clique and 0 otherwise. This model is equivalent to the clique factorization model given above, if $N_k=|\operatorname{dom}(C_k)|$ is the cardinality of the clique, and the weight of a feature $f_{k,i}$ corresponds to the logarithm of the corresponding clique factor where is the i-th possible configuration of the k-th clique, i.e. the i-th value in the domain of the clique C_k.

The probability P is often called the Gibbs measure. This expression of a Markov field as a logistic model is only possible if all clique factors are non-zero, i.e. if none of the elements of $\mathcal{X}$ are assigned a probability of 0. This allows techniques from matrix algebra to be applied, e.g. that the trace of a matrix is log of the determinant, with the matrix representation of a graph arising from the graph's incidence matrix.

The importance of the partition function Z is that many concepts from thereby be gained. In addition, the partition function allows variation methods to be applied to the solution of the problem: one can attach a driving force to one or more of the random variables, and explore the reaction of the network in response to this perturbation. Thus, for example, one may add a driving term J_v, for each vertex v of the graph, to the partition function to get:

Formally differentiating with respect to J_v gives the expectation value of the random variable X_v associated with the vertex v:

Correlation functions are computed likewise; the two-point correlation is:

Log-linear models are especially convenient for their interpretation. A log-linear model can provide a much more compact representation for many distributions, especially when variables have large domains. They are convenient too because their negative log likelihoods are convex. Unfortunately, though the likelihood of a logistic Markov network is convex, evaluating the likelihood or gradient of the likelihood of a model requires inference in the model, which is in general computationally infeasible.

III. GAUSSIAN MARKOV RANDOM FIELDS

3.1. Definition:

The Markov property on a spatial cross section infers spatial reliance communicated restrictively, which permits naturally engaging site-by-site demonstrate building. There are also cases, such as in biological network analysis, where the Markov property has a deep scientific significance. In addition, the model is regularly vital for computational effectiveness of Markov chain Monte Carlo calculations. Here, we introduce a new criterion to fit a GMRF to a given Gaussian field, where the Gaussian field is characterized by its spatial covariance's

A Gaussian field X on a finite lattice D is a Gaussian random vector of length $|D|\equiv n$ with mean μ and covariance matrix. The precision matrix of X is $R =-1$. If L(X) denotes the distribution of the variable X, then for a Gaussian field, $L(X) = N(\mu,E)$; equivalently, we can write

$$X = (X1...Xn) \sim N(\mu,E) .$$

We shall be concerned mostly with zero-mean Gaussian fields, which are characterized by with entries given by pairwise covariance's, {cov(Xi,Xj)}. In the spatial setting, such as for radionuclide concentrations on Rongelap Island this often involves specifying a spatial covariance function [2]. In exchange for this simple spatial-model specification, modeling dependence in terms of R can lead to considerable computational speed-ups.

Let G = (V,E) be an undirected graph, where V is the set of vertices and E is the set of edges. In the spatial setting, V = D, the spatial area, and for any site I ∈ V , N(i) is the arrangement of neighbors of I characterized by those destinations j ∈ V associated with I by an edge in E. Let XN(i) denote the random vector of those Xj, where j ∈ N(i). The notation i ~j, for i and j two sites in V means that i and j are neighbors. One final piece of notation is needed. Let Sn denote the set of all symmetric n × n matrices, S+n denote the set of all positive-semi definite symmetric n × n matrices, and S++n denote the set of all positive-definite symmetric n × n matrices.

3.2 Properties of a GMRF

Consider the irregular vector X recorded by the vertices of an non-directed diagram G. The Markov property on the graph G = (V, E) states that if a, b ∈ V and there is no edge between a and b, then Xa is conditionally independent of Xb, given all remaining variables XV \{a,b}. A finite Markov random field is a random vector that follows the Markov property with respect to a given graph. More details about Markov random fields can be found. As a special case, the GMRFs are particularly appealing, since we can obtain their joint distribution in closed form and they are characterized by their precision matrix (equivalently by their covariance matrix). Moreover, they have the appealing property that the underlying graph is easily obtained from the pattern of zeros in the precision matrix. A GMRF is a limited Markov arbitrary field whose joint appropriation is Gaussian. There is a proportional definition, which is more suggestive of the approach created in this paper.

IV. FUZZY LOGIC

4.1 DEFINITION OF FUZZY LOGIC:

Fluffy logic is a numerical rationale that endeavors to take care of issues by doling out qualities to an uncertain range of information keeping in mind the end goal to land and no more precise conclusion conceivable. Here, the fuzzy logic is used to conclude whether a pixel is an edge pixel or not. The proposed technique begins by fuzzyfying the gray values of a pixel into two fuzzy variables, namely the black and the white. Fuzzy rules are defined to find the edge pixels in the fuzzified images.The term "fuzzy logic" was introduced with the proposal of fuzzy set theory by Lotfi A. zadeh. Fuzzy logic can be implemented to many fields, ranging from control theory to artificial intelligence. This Fuzzy logic uses Edge detection method to find the weed edge pixels, by applying the rules to each pixel along with its 8-neighbourhood. Before applying the tenets, every pixel is arranged into a "white" and "dark" pixel utilizing the triangular participation work.

4.2Fuzzy with Edge detection:

Edge detection plays a vital role in many of the applications of image processing such as pattern recognition and image segmentation. Edges relate to sharp varieties of picture power and pass on essential data in a picture. Edges are framed from pixels with subsidiary esteems that surpass a pre-set edge. Edge detection not only extracts the edges of the interested objects from an image, but it also forms the basis for image fusion, shape extraction, image matching, image tracking

Normally, the edge detection methods use the gradient of images and arithmetic operators. The most popular edge detection methods, such as Sobel, Prewitt, Roberts etc. detect edges using a first-order derivative of intensity since they consider edges to be a set of pixels where there is an abrupt change in the intensity of the gray level. These edge detection methods do not consider the neighborhood of a pixel, while in our proposed technique assumes a vital part in edge identification. Then again, fluffy rationale utilizes basic if-then principles, which don't require any thresholding or complex angle based counts. Thus, an edge detection method that is based on fuzzy logic is proposed in our paper. Here are a lot of ways to detect edges using fuzzy image processing. But the simplest way is to fuzzify the image. This involves finding the membership value of each pixel for a particular set and then applying the defined rules to the fuzzified image to find the edge map. If the information in a database is inexact, incomplete, or not entirely certain, then the systematic use of fuzzy logic becomes practically indispensable. In many image processing applications, the image information that is to be processed is uncertain and imprecise. In the proposed approach, the question of whether a pixel is darker or brighter comes under the realm of fuzzification. The darker pixels are placed in the black class, whereas, the brighter ones are put in the white class. In order to fuzzify the image, the membership of each pixel is found by using the triangular membership function. The membership function of an element defines the degree to which that element belongs to the fuzzy set. The value of the membership function always lies between [0…1].

4.3 Fuzzy Rules:

Individuals settle on choices in view of principles. The choice and the methods for picking that choice are supplanted by fluffy sets and the guidelines are supplanted by fluffy standards. A fuzzy rule is defined as a conditional statement in the form of:

IF x is A
THEN y is B

Where x and y are etymological factors, An and B are semantic esteems that are dictated by fluffy sets on the universe of the talk X and Y, individually. The fuzzy rules used in the proposed edge detection approach take into account the linguistic values of the 8-neighborhood of the pixel that is under consideration. Here, the linguistic values can be white or black. The fuzzy rule is a control system that is used to infer decisions to construe choices from a learning base. The knowledge base to infer the edge pixel in an image is the pixel with its 8-neighborhood. The decision whether each pixel is an edge pixel or not is made by using the fuzzy rules that are applied to the 8-neighborhood. The pixels in the 8-neighborhood of a pixel may be black or white.

V. IMAGE MODEL

The weed "Rumex Obtusifolius" can be detected by using the GMRF but, this approach cannot detect the noisy images and so to overcome this drawback, we developed here a new algorithm that uses edge detection with fuzzy logic along with GMRF property.

In this newly developed algorithm first we take an RGB color image of size MxN and convert it to grayscale image. Then apply the fuzzy logic. For this we need to take histogram of the grayscale image. Based on this we have to select the fuzzy variables 'a' and 'c' manually. Now apply the fuzzy rules. Then convert the matrix image into grayscale image.

Now GMRF property is to be applied. For this every time take two 3x3 matrices and find the absolute difference between the pixels of two matrices. If it is equals to 1 then compute s. Otherwise compute s1. Combining s and s1 calculate new matrix v.

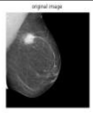
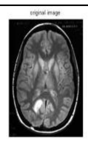
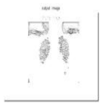
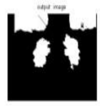
Then convert this into grayscale image and finally we get an output image which consists of weed only. This approach can even detect the images that are corrupted by noise.

VI. PERFORMANCE MEASUREMENT

To compare the performance of the proposed method with the existing method, here we add two types of noises for both existing method and the proposed method. The two types of noises are:-

1. Gaussian noise
2. Salt & Pepper noise.

After adding these two noises we compare the original image with the noise added image. Now draw the graph for two noises by noting their values. This process is same for both existing and proposed methods. Their results are as shown in below figures.

Original Image	**GMRF Output**	**Fuzzy Logic Output**	**Threshold Value for Fuzzy Logic (a, c)**
			120,170
			245,170
			120,170
			70,170
			100,90

Tab 1: Comparison of GMRF and Fuzzy Logic Method with Different Threshold Values

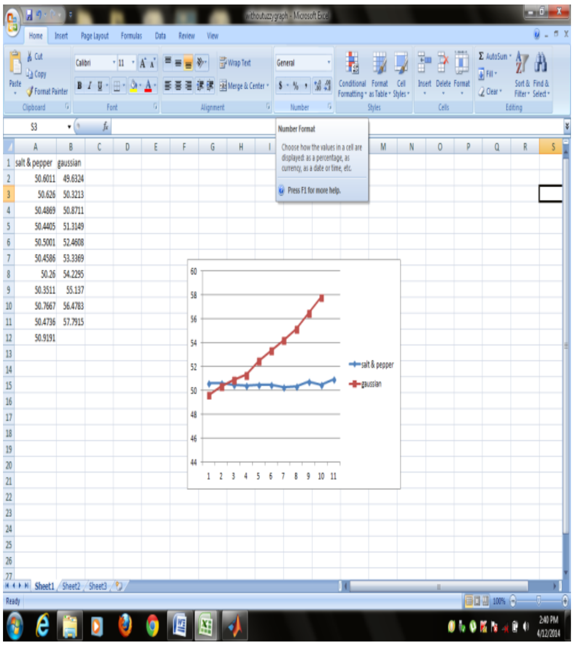


Fig: 2 Gaussian and Salt & Pepper noises for the existing method.

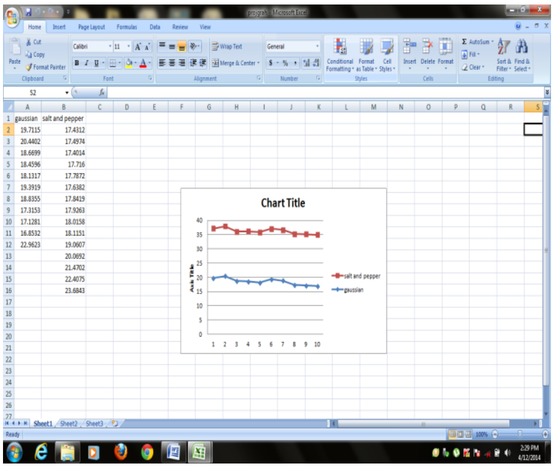


Fig: 3 Gaussian and Salt & Pepper noises for the proposed method.

VII. CONCLUSION

This project can successfully detect the weed 'Rumex Obtusifolius 'which can be used in robotic systems. So through this project we can clearly show that our proposed method will give satisfactory results compared to the existing method. And also this is suitable for detection of images that are corrupted by noises, Moreover this project is suitable for various general application purposes like in detecting the tumors in MRI scanned images and in other applications as said previously.

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