Construction of Fuzzy Linear Space Based Field Operation Lines for Agricultural Machinery

Đorđe Obradović, Zora Konjović, Endre Pap, and Vuk Malbaša

Abstract— **Effective utilization of agricultural machinery significantly affects the economy of agricultural production, food security/safety, and environment.**

In this paper we present a novel approach to creation of field operation lines, which considers imprecisions in data.

The operation lines construction bases on fuzzy representation of geo-spatial data, and linear models obtained by bagging and ensemble methods of machine learning. For representing imprecision in geo-spatial data we use a simple but yet efficient data model based on fuzzy linear space. We train our models using the training set consisted of machine positions acquired via GPS device.

Index Terms—**agriculture, machinery, operation line, machine learning, fuzzy linear space.**

I. Introduction

Efficient agricultural production is achieved by means of high level of operation mechanization and automation, which presumes careful planning and tracking. Geo-spatial data play an extremely important role in both transporting units navigation and control of a primary unit (primary unit is an equipment that performs agricultural operation).

On the other hand, such data are collected using various sensors that are all prone to measurement errors and, therefore, provide a data with limited accuracy and precision. Improvements in the accuracy and affordability of the GPS (Global Positioning System) sensors have led to a wide adoption of this technology in many fields, especially in crops production even tough GPS technology is not an exemption to above mentioned data imprecision problem.

Research in vehicle tracking, agriculture operations recording and precision farming has gained attention of both commercial and scientific communities. For example, companies like Trimble and TopCon, which are known for developing positioning devices, also develop positioning tools designed to help farmers in everyday tasks. Services have also been developed to collect data from mechanization, process it into suitable form and present it to the end users (farmers). However, existing tools are expensive and not available to most farmers.

On the other hand, a significant amount of research was done on path tracing from GPS data, forming a solid base for the development of sophisticate yet inexpensive devices.

This paper presents a proposal that enables creation of operation lines (spatial trajectories that should be tracked by a machinery performing certain operation) that can be used for navigating agriculture machinery in operation as well as monitoring the machine motion that actually takes place during operation. Thereby, our approach tries to cope with data imprecision problem by using a simple, compact spatial data model based on a fuzzy linear space.

The rest of this paper consists of four sections. The first of them brings an overview of current research related to the problem addressed by this paper. The second one presents methodology used in our research, while the third section presents experimental results. The fourth section contains conclusions and directions for future work.

II. Related work

In this section the research results are presented that are related to the research subject of this paper. They are analyzed with regard to several aspects that include ICT (information and Communication Technology) enabled field operation planning emphasizing geo-spatial issues, machine learning applications to agriculture, and modeling imprecise geo-spatial data.

The paper [1] gives a brief overview of technologies relying upon satellite navigation that are important enablers for ICT based agriculture. In this paper, Bochtis recognizes four operational systems heavily relying upon satellite based technologies: Precision agriculture management systems, Robotic systems, Fleet management systems and Planning systems. All these systems require spatially characterized data.

Planning systems are mainly related to field area coverage, highlighting mission planning system of an autonomous agricultural vehicle, and route planning for supporting units. This very same problem is the subject of numerous other research papers [2 – 11] dealing with more specific issues like transport optimization, obstacles avoidance, specific operations planning, harvesting operation optimization, operational planning algorithms, autonomous vehicles, algorithms for computing off-target application area, optimal path planning, improvement of machinery efficiency and performance of agricultural field operations.

Machine learning applications to agriculture problems gain an increasing attention of research community for quite a long time. Indeed they are becoming expressly attractive with wide availability and affordability of technologies that enable acquisition of large amounts of diverse data related to agricultural production. Numerous papers propose different

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machine learning techniques for solving agricultural problems. Most frequently machine learning applications in agriculture encompass tasks like crop yield prediction [12 - 16], land use mapping and forecasting [17 - 20], land cover mapping [21 - 24].There are also papers (less frequent) that apply machine learning to agriculture machinery operation [25 - 29]. Examples of papers applying boosting and bagging algorithms to agricultural problems are evaluating influences on groundwater hydrochemistry [30], and irrigation modelling [31].

Concerning spatial data uncertainty/imprecision there are three basic approaches: exact models, probabilistic models, and fuzzy models [39]. Fuzzy models [32–39] deal with defining fuzzy spatial data types, such as fuzzy points, fuzzy lines and fuzzy regions [32, 39], fuzzy geometry [33, 35, 39], objects which do not have homogeneous interiors and sharply defined boundaries [35], and spatial data types in data bases [36, 37,38].

III. The Methodology

Main elements of our methodology are the data model, which relies upon the results of the paper [39], and a novel algorithm used for constructing a set of fuzzy lines from the set of temporally ordered fuzzy points acquired by GPS sensing.

A. Data model

Our data model consists of two geometric elements, a *fuzzy point* and a *fuzzy line*.

Definition 1 *Fuzzy point* $P \in \mathbb{R}^2$, denoted by $\tilde{P}$ is defined by its membership function $\mu_{\tilde{P}} \in \mathcal{F}^2$**,** where the set $\mathcal{F}^2$ contains all membership functions $u: \mathbb{R}^2 \to [0,1]$ satisfying following conditions:

i) $(\forall u \in \mathcal{F}^2)(\exists_1 P \in \mathbb{R}^2)\, u(P) = 1$,
ii) $(\forall X_1, X_2 \in \mathbb{R}^2)(\lambda \in [0,1])\, u(\lambda X_1 + (1-\lambda)X_2) \geq \min\big(u(X_1), u(X_2)\big)$,
iii) function u is upper semi continuous,
iv) $[u]^\alpha = \{X | X \in \mathbb{R}^2, u(X) \geq \alpha\}$ α-cut of function u is convex.

The point from $\mathbb{R}^2$, with membership function $\mu_{\tilde{P}}(P) = 1$, will be denoted by P (P is the core of the fuzzy point $\tilde{P}$), and the membership function of the point $\tilde{P}$ will be denoted by $\mu_{\tilde{P}}$. By $[P]^\alpha$ we denote the α-cut of the fuzzy point (this is a set from $\mathbb{R}^2$).

Definition 2 $\mathbb{R}^2$ *Linear fuzzy space* is the set $\mathcal{H}^2 \subset \mathcal{F}^2$ of all functions that, in addition to the properties given in Definition 1, are:

i) Symmetric against the core $S \in \mathbb{R}^2$
$(\mu(S) = 1)$,
$\mu(V) = \mu(M) \wedge \mu(M) \neq 0 \Rightarrow d(S,V) = d(S,M)$,
where $d(S,M)$ is the distance in $\mathbb{R}^2$.
ii) Inverse-linear decreasing w.r.t. points' distance from the core according to:

If $r \neq 0$

$$\mu_{\tilde{S}}(V) = \max\left(0, 1 - \frac{d(S,V)}{|r_S|}\right),$$

if $r = 0$

$$\mu_{\tilde{S}}(V) = \begin{cases} 1 & if \quad S = V \\ 0 & if \quad S \neq V \end{cases},$$

where $d(S,V)$ is the distance between the point V and the core S ($V, S \in R^n$) and $r \in \mathbb{R}$ is constant.

Elements of that space are represented as ordered pairs $\tilde{S} = (S, r_S)$ where $S \in \mathbb{R}^2$ is the core of $\tilde{S}$, and $r_S \in \mathbb{R}$ is the distance from the core for which the function value becomes 0.

Definition 3 Let $\tilde{A}, \tilde{B} \in \mathcal{H}^2$. An operator $+: \mathcal{H}^2 \times \mathcal{H}^2 \to \mathcal{H}^2$ is called *fuzzy points addition* and is given by

$$\tilde{A} + \tilde{B} = (A + B, r_A + r_B), \tag{1}$$

where $A + B$ is a vector addition, and $r_A + r_B$ is a scalar addition.

Definition 4 Let $\mathcal{H}^2$ be a linear fuzzy space. Then a function $f: \mathcal{H}^2 \times \mathcal{H}^2 \times [0,1] \to \mathcal{H}^2$ is called *linear combination* of the fuzzy points $\tilde{A}, \tilde{B} \in \mathcal{H}^2$ and is given by

$$f\big(\tilde{A}, \tilde{B}, u\big) = \tilde{A} + u \cdot \big(\tilde{B} - \tilde{A}\big), \tag{2}$$

where $u \in [0,1]$ and operator $\cdot$ is a scalar multiplication of fuzzy point.

Definition 5 Let $\mathcal{H}^2$ be a linear fuzzy space and function f a linear combination of the fuzzy points $\tilde{A}$ and $\tilde{B}$. Then a fuzzy set $\widetilde{AB}$ is called *fuzzy line* if the following holds

$$\widetilde{AB} = \bigcup_{u \in [0,1]} f(\tilde{A}, \tilde{B}, u). \tag{3}$$

A. Fuzzy line construction algorithm

Having the data model described above, and a set of data collected by GPS sensing, we represent the data as fuzzy points (each point represented by three double values: x, y – spatial coordinates, r-accuracy of measurement), and operation lines as fuzzy lines. So, we reduce the problem of determining operation lines to the problem of a fuzzy line construction.

For the fuzzy line construction we have developed an algorithm that constructs a linear model of the line by randomly taking two points from training sets representing starting and ending line points. Further, by generating a sufficient number of examples, an ensemble of simple linear models is generated and the final solution is obtained by averaging these linear models.

The algorithm is given by the following pseudo code.

Input: ordered set of GPS points' coordinates, r – GPS sensor accuracy;
Output: fuzzy line $\widetilde{CD}$
Algorithm:

1. Data preprocessing/preparation
   - Convert input data from spherical coordinate system (lon,lat) to metric system.
   - Create a list of temporally ordered list of fuzzy represented points (each object contains three double values: x, y – spatial coordinates, r- measurement accuracy).
2. Training:
   Create a training sets: randomly choose n points from set of input data and form the sets TrA and TrB (A is the line starting point, while B is the line ending point).

   listW=[]
   listB=[]
   for $\tilde{A} \in TrA$, $\tilde{B} \in TrB$ and $\tilde{A} \neq \tilde{B}$, do:
   $$w' = \frac{y_A - y_B}{x_A - x_B}$$
   $$b' = y_A - w' x_A$$
   listW.append(w'),
   listB.append(b')
   $w = avg(listW)$;
   $b = avg(listB)$;
   $w_r = stdev(listW)$;
   $b_r = stdev(listB)$;

   where $\widetilde{W} = (w, w_r)$ is a fuzzy slope and $\tilde{B} = (b, b_r)$ is a fuzzy bias.
3. Determine fuzzy points $\tilde{C}$ and $\tilde{D}$ using the following formulae:
   $$\tilde{C} = \widetilde{W} \cdot x_{min} + \tilde{B}$$
   $$\tilde{D} = \widetilde{W} \cdot x_{max} + \tilde{B}$$
   where x_{min} and x_{max} are minimal and maximal values in x dimension.
   Fuzzy points $\tilde{C}$ and $\tilde{D}$ determine resulting fuzzy line.

Pseudo code of the algorithm for fuzzy line construction

IV. Experimental Results

In this section we show the experimental results obtained by the algorithm proposed in the section III of this paper (denoted as FS), method that applies CG (Computational Graph) with a linear model trained by ADAM (A Method of Stochastic Optimization) optimizer (denoted as CG), and classical polynomial fit method (denoted as polyfit).

We compare these three methods against *accuracy* and *execution time*.

In our experiment we used the data consisting of 194 sets (manually annotated as lines) of GPS points.

The number of points per line is not equal for each line. It varies from 10 to 220.

Figure 1 shows the structure of our sample regarding the number of points per line.

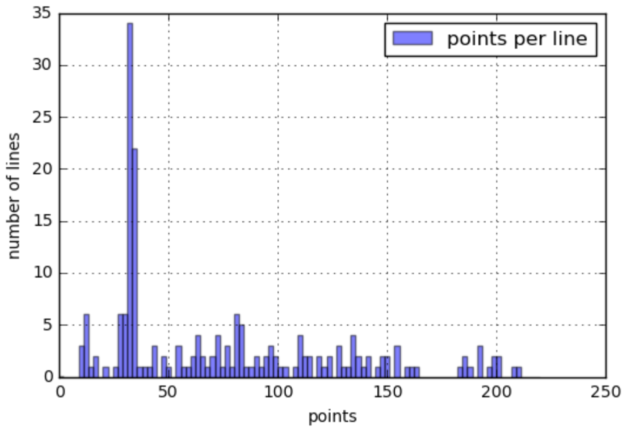

Figure 1. Number of points per line

Graphs shown on Figures 1 and 2 present differences in bias and slope of the lines obtained by polyfit. CG, and FS methods.

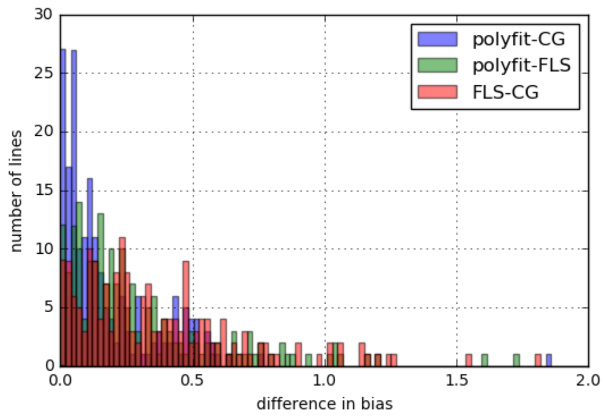

Figure 2. Differences in bias B for polyfit vs. CG, polyfit vs. FLS, and FLS vs. CG methods

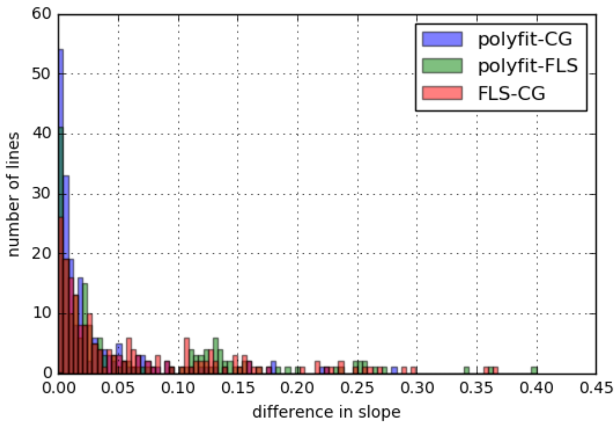

Figure 3. Differences in slope W for polyfit vs. CG, polyfit vs. FLS, and FLS vs. CG methods

The results that are obtained indicate that no significant difference exists in accuracy between these three methods, i.e., FLS method gives results which are comparable with those obtained by methods based on computational graph and gradient training.

Execution time for 194 examples was measured on the same computer I5 Intel processor with 8GB RAM, and Linux Ubuntu OS. The CG example was implemented using the *Tensorflow* package. The polyfit algorithm was implemented using the *NumPy* package.

Figure 4 shows the execution times for classical polyfit and FLS algorithms.

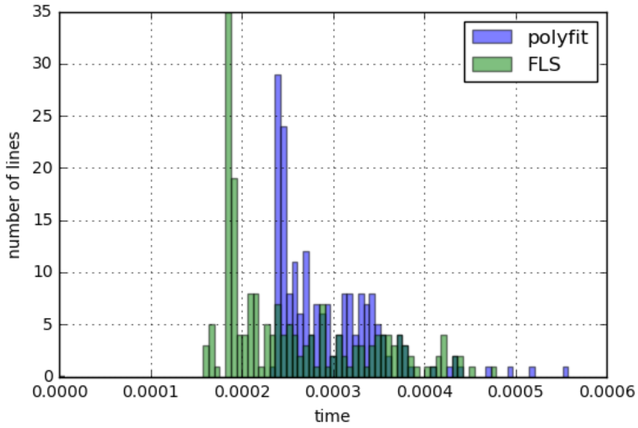

Figure 4. Execution times for classical polyfit and FLS algorithms

As indicated by this diagram, the proposed method outperforms standard polyfit method in most cases. The number cases for which polyfit outperforms FLS is smaller, and cases correspond to the lines consisting of small number of points.

Figure 5 presents execution times of all three methods. From this diagram one can catch sight of significantly higher execution times for the CG method. These results are expected due to the fact that no platform supporting GPU (Graphics Processing Unit) acceleration was used in our experiments. Use of such platform would for sure speed up CG, but one can hardly expect to reach hundred times faster calculations, which is the difference in speed obtained in this example.

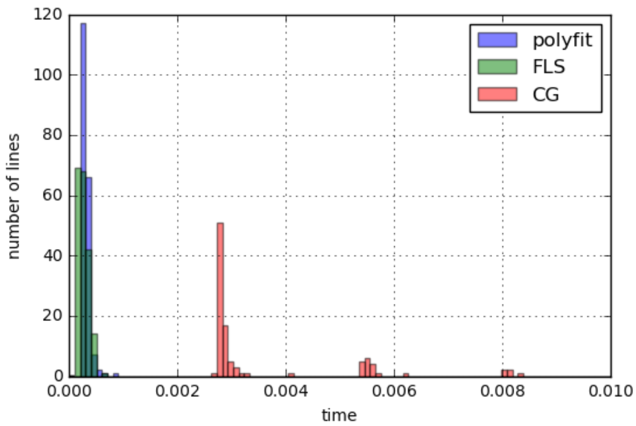

Figure 5 Execution times for classical polyfit, CG and FLS algorithms

Therefore, our experiments indicate that the proposed method outperforms other two methods in execution time while keeping the accuracy for the situations when the number of points constituting a line is larger, which is the case in practical applications.

V. CONCLUSION

Effective utilization of agricultural machinery significantly affects the economy of agricultural production, food security/safety, and environment. Planning of machinery motion trajectories, which is absolutely necessary for efficient utilization of such machinery for both transporting units' navigation and primary units' control, requires geo-spatial data that can be collected using GPS sensing. On the other hand, such data are prone to measurement errors and, therefore, provided with limited accuracy and precision.

In this paper we present a novel approach to a creation of field operation lines, which considers imprecisions in data.

The operation lines construction bases on fuzzy representation of geo-spatial data, and linear models obtained by bagging and ensemble machine learning methods.

We have compared the results of the algorithm proposed in this paper with results obtained by methods based on computational graph and gradient training. The results that are obtained indicate that the proposed algorithm has a capacity to outperform computational graph based methods for the situations that better comply with real life demands.

Future work should be directed towards investigation of the proposed algorithm's performance especially in terms of number of points per line, further improvements of the data model including extension to 3D space modelling, and non-spatial data inclusion.

Yet another task for the future is investigation of application of other machine learning methods to agricultural machinery control synthesis.

Finally, the last but not least important is the practical implementation of standardized filed operation maps that could be used by machinery manufactured by different manufacturers.

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