Review of research on agricultural vehicle autonomous guidance

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Abstract: A brief review of research in agricultural vehicle guidance technologies is presented. The authors propose the conceptual framework of an agricultural vehicle autonomous guidance system, and then analyze its device characteristics. This paper introduces navigation sensors, computational methods, navigation planners and steering controllers. Sensors include global positioning systems (GPS), machine vision, dead-reckoning sensors, laser-based sensors, inertial sensors and geomagnetic direction sensors. Computational methods for sensor information are used to extract features and fuse data. Planners generate movement information to supply control algorithms. Actuators transform guidance information into changes in position and direction. A number of prototype guidance systems have been developed but have not yet proceeded to commercialization. GPS and machine vision fused together or one fused with another auxiliary technology is becoming the trend development for agricultural vehicle guidance systems. Application of new popular robotic technologies will augment the realization of agricultural vehicle automation in the future.

Keywords: agricultural vehicle, guidance, machine vision, GPS

DOI: 10.3965/j.issn.1934-6344.2009.03.001-016

Citation: Ming Li, Kenji Imou, Katsuhiro Wakabayashi, Shinya Yokoyama. Review of research on agricultural vehicle autonomous guidance. Int J Agric & Biol Eng, 2009; 2(3): 1－16.

1 Introduction

Over history, agriculture has evolved from a manual occupation to a highly industrialized business, utilizing a wide variety of tools and machines[1]. Researchers are now looking towards the realization of autonomous agricultural vehicles. The first stage of development, automatic vehicle guidance, has been studied for many years, with a number of innovations explored as early as the 1920s[2,3]. The concept of fully autonomous agricultural vehicles is far from new; examples of early ‘driverless tractor’ prototypes using leader cable guidance systems date back to the 1950s and 1960s[4].

In the 1980s, the potential for combining computers with image sensors provided opportunities for machine vision based guidance systems. During the mid-1980s, researchers at Michigan State University and Texas A&M University were exploring machine vision guidance. Also during that decade, a program for robotic harvesting of oranges was successfully performed at the University of Florida[5]. In 1997, agricultural automation had become a major issue along with the advocacy of precision agriculture. The potential benefits of automated agricultural vehicles include increased productivity, increased application accuracy, and enhanced operation safety. Additionally, the rapid advancement in electronics, computers, and computing technologies has inspired renewed interest in the development of vehicle guidance systems. Various

Received date: 2009-07-20 **Accepted date**:2009-08-30

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guidance technologies, including mechanical guidance, optical guidance, radio navigation, and ultrasonic guidance, have been investigated[6,7].

Table 1 summarizes examples of research systems that have been developed around the world. Autonomous navigation system for agricultural vehicles is now regarded as an important advance in precision agriculture and a promising alternative to the dwindling farming labor force, in addition to satisfying the quest for higher production efficiency and safer operation [6, 8].

Table 1 Examples of guidance systems developed around the world

Institute (Country)	Sensor	Machine or test device	Performance results	Literature
University of Illinois, USA	Machine vision, GPS, GDS	Case 8920 MFD and 2WD Tractors	Vision guidance at 16 km/h on row crops	Zhang[9,10] Benson[11,12]
Stanford University, USA	GPS	John Deere 7800 Tractor	1° accuracy in heading, line tracking accuracy with 2.5 cm deviation	O'Connor[13]
University of Florida, USA	GPS, laser radar	Tractor	Average error of 2.8 cm using machine vision guidance and average error of 2.5 cm using radar guidance	Subramanian[14]
University of Halmstad, Sweden	Machine vision, Mechanical sensor, GPS	Tractor with row cultivator	Standard deviation of position of 2.7 and 2.3 cm	Åstrand[15,16]
Bygholm Research Center, Denmark	Machine vision	Tractor	Accuracy of less than 12 mm	Søgaard[17]
University of Tokyo, Japan	FOG, Ultrasonic Doppler sensor	Tractor (Mitsubishi Co.)	Lateral displacement from the reference line was less than 10 cm at speeds of 0.7 to 1.8 m/s on a straight line	Imou[18]
National Agriculture Research Center, Japan	RTK GPS, FOG	PH-6, Iseki Co., Ehime transplanter	Less than 12 cm, yaw angle offset of about 5.5 cm at 2.52 km/h	Nagasaka[19]
BRAIN, Japan	Machine vision and laser range sensor	Tractor	Error about 5 cm at the speed of 0.4 m/s	Yukumoto[20]
Hokkaido University, Japan	GDS, laser scanner	Tractor	Average error less than 1 cm	Noguchi[21,22]
National Centre for Engineering in Agriculture, Australia	Machine vision	Tractor	Accuracy of 2 cm	Billingsley[23]

Research on autonomous agricultural vehicles has become very popular, and the robotics industry has developed a wide range of remarkable robots. In the near future, farmers will be using affordable, dependable autonomous vehicles for agricultural application.

Section 2 includes an analysis of the device characteristics of agricultural vehicle guidance systems. A brief overall review of the past 20 years of global research in agricultural vehicle guidance technologies is presented in terms of a framework for agricultural vehicle autonomous guidance systems, as shown in Figure 1. The key elements are navigation sensors, computational methods, navigation planners and steering controllers. The final section addresses some of the barriers to development and discusses the potential for new development.

2 Features of agricultural vehicle devices

The agricultural environment offers a very different set of circumstances from that encountered by a laboratory mobile robot. In one respect, operation is simplified by the absence of clutter typically present in the indoor environment; however, a number of additional complications are raised. For example, the operating areas are large; ground surfaces may be uneven; depending on the operation, and wheel slippage may be far from negligible. Cultivation may interfere with underground cables, colors may change with plant growth, and soil quality may vary. Environmental conditions (rain, fog, dust, etc.) may affect sensor function; moreover, a low-cost system is required.

These disadvantages make it more difficult to realize agricultural automation. Companies are unwilling to invest in commercialization because it is not seen as a worthwhile money-making venture, and farmers are not financially able to participate. Other major reasons include the need to improve the technology and decrease the cost [24].

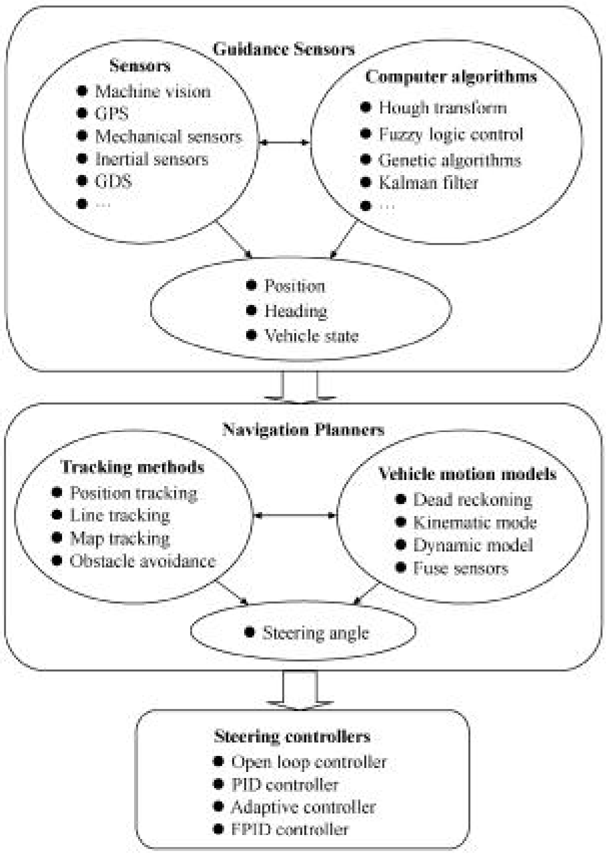


Figure 1 Framework of agricultural vehicle autonomous guidance system

Compared with these complicating factors, agricultural farm fields have several advantages for developing autonomous guidance systems. For example, the working areas generally do not change; landmarks can be easily set up around the corners of a field and be taken as a stationary environment. The crops are always the same plants at the same places and can be easily distinguished. Therefore, even though there are more disadvantages than advantages for realizing agricultural vehicle autonomous guidance, there are enough research achievements to promote its development.

3 Navigation sensors

3.1 Machine vision

Machine vision sensors measure the relative position and heading using the image sensor mounted on the vehicle. There are several aspects of machine vision based sensing. Different types of sensor modalities can be selected to measure the guidance information. Positioning of the sensor on the vehicle requires an understanding of the geometric relationship between the image sensor, the vehicle and the field-of-view that the sensor uses for guidance information. Figure 2 shows one example. Researchers have explored the use of vision sensors for detecting a guidance directrix on row crops, soil tillage, and the edges along harvested crops. Various methodologies of image processing have been investigated for extracting the guidance information. The processed images provide output signals that can be used to provide steering signals for the vehicle.

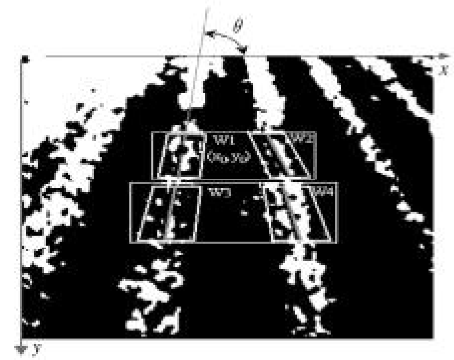


Figure 2 Row detection via segmented binary image [25]

One of the most commonly used machine vision methods is for detecting a guidance directrix on row crops, soil tillage, and the edges along harvested crops. Benson[12] developed a guidance combine harvester based on the lateral position of the crop cut edge. Marchant and Brivot[26] used the Hough transform for row tracking in real time (10 Hz) and noted that their technique was tolerant to outliers (i.e., weeds) only when their number was reasonably small compared to the number of true data points. Marchant [27] reported an overall RMS error of 20 mm in the lateral position at a travel speed of 0.7 m/s using this technique to guide an agricultural vehicle in a transplanted cauliflower field.

The threshold method has been applied in many vision applications to separate objects of interest from imagery. For reliably extracting crop row features from field images, the major challenge of the threshold method is the difficulty in determining an adequate effective threshold value under varying ambient light conditions or changing crop growth stages. The effectiveness of distinguishing crops from weeds is another challenge in determining a pathway using the obtained field images.

Research has been reported on attempts to improve the reliability of crop feature extraction and pathway determination for vision-based guidance systems. Hague and Tillett [28] exploited a method using a bandpass filter to attenuate the grey level of weeds and shadows in field images. Pinto et al.[29] attempted to apply the principal component analysis method to extract crop row features from field images. Søgaard and Olsen[7] also developed a machine vision guidance method that did not require a plant segmentation step, replacing it with a less intensive computation of the center of gravity for row segments in the image and weighted linear regression to determine the position and orientation of the rows.

Han et al. [25] developed a row segmentation algorithm based on *k*-means clustering to segment crop rows. This information was then used to steer a tractor. The guided tractor was able to perform field cultivation in both straight and curved rows. Okamoto et al. [30] developed an automatic guidance system for a weeding cultivator. A color CCD camera acquired the crop row images, which were then processed by computer and used to determine the offset between the machine and the target crop row.

Other techniques and systems have been investigated for machine vision guidance, and many of them have improved the robustness and dependability of machine vision. Yukumoto et al.[20] developed a tillage robot with vision and laser range sensor. They used laser sensor to improve the robustness. Billingsley and Schoenfisch[23] reported a vision guidance system that is relatively insensitive to additional visual 'noise' from weeds. They used linear regression in each of three crop row segments and a cost function analogous to the moment of the best-fit line to detect lines fitted to outliers (i.e., noise and weeds) as a means of identifying row guidance information. They showed that their system is capable of maintaining an accuracy of 2 cm.

Tillett and Hague[31] developed a machine vision guidance system for cereal crops, using the midpoints of 15 rows extracted from a single view of three adjacent crop rows (five midpoints per row). They tested the system in a single barley field with light to moderate weed pressure under uniform natural lighting and obtained a standard error in hoe position of 13 mm at travel speeds up to 6 km/h. Hague and Tillett [28] used the analysis of the periodic near-infrared intensity function in a lateral path across five wheat rows in a plane view of the field rather than a traditional row segmentation method to obtain row guidance information. They obtained a root-mean-square (RMS) position error of 15.6 mm at a travel speed of 5.8 km/h.

For more complete crop or field information, some researchers used a stereovision system to provide a three-dimensional (3D) field image by combining two monocular field images taken simultaneously from a binocular camera. Such 3D images are reconstructed based on the different-disparity monocular images to decrease the ambient light influence. Kise et al.[32] developed a stereovision-based agricultural machinery crop-row tracking navigation system. The RMS error of lateral deviation was 3–5 cm following both straight and curved rows at speeds up to 3.0 m/s. The method required some weed-free areas to provide sufficient information for detecting the navigation points.

Åstrand and Baerveldt[16] developed a machine vision guidance system that achieved good performance in detecting plants in near-infrared images acquired under non-uniform natural illumination by performing grayscale opening on the raw near-infrared image and subtracting it from the original prior to segmentation. Their method, based upon the Hough transform, used multiple rectangular regions (one for each row viewed) with the rectangle width adjusted for crop size. The information from multiple rows was fused together to obtain a common estimate of the row position. The accuracy of position estimation was less than 1.2 cm with a standard error depending on plant size. Field tests showed that the system had sufficient accuracy and speed to control the cultivator and mobile robot in a closed-loop fashion with a standard deviation of position of 2.7 and 2.3 cm, respectively, with incomplete row structures due to missing plants combined with high weed pressure (up to 200 weeds/m^2).

Kaizu and Imou [33] developed a dual-spectral camera system, shown as Figure 3, for paddy rice seedling row detection. The system used a pair of low-cost monochrome cameras with different spectral filters. It matched a near-infrared image and a red image and it worked in the strong reflections on the water surface under cloudy conditions from morning to dusk.

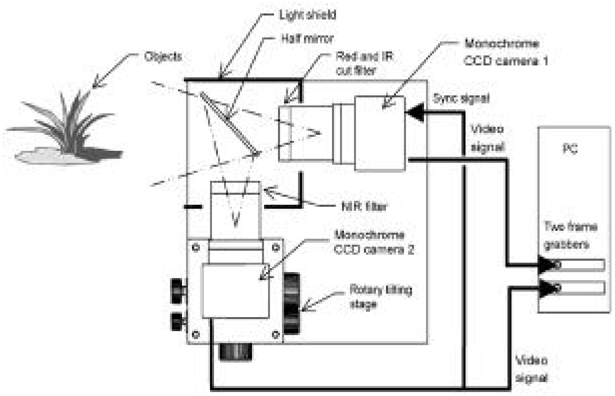


Figure 3 Schematic diagram of dual-spectral camera system[33]

3.2 Global positioning system

Since the early 1990s, Global Positioning System (GPS) receivers have been widely used as global guidance sensors[34-37]. GPS-based guidance technology can be used for many field operations such as sowing, tilling, planting, cultivating, weeding and harvesting[38,39]. GPS-based navigation systems are the only navigation technologies that have become commercially available for farm vehicles. Many tractor manufacturing companies now offer the Real-Time Kinematic (RTK) GPS based auto steering system as an option on their tractors. The position information from the RTK GPS can be used for both guidance and other applications such as seed mapping, traffic control, and tillage control. GPS guidance systems provide an absolute guidance system in contrast to the relative guidance provided by machine vision, which requires that the crop be planted using a GPS-guided planting system or the crop rows mapped using some type of geo-referenced mapping technique. GPS guidance systems also require that a GPS base station be located within approximately 10 km of the RTK GPS guided tractor or agricultural robot. However, since GPS systems do not depend upon the visual appearance of the crop, they are not adversely affected by weed density, shadows, missing plants or other conditions that degrade the performance of machine vision guidance systems. Another advantage of GPS guidance systems is that they can be easily programmed to follow curved rows[40].

There appear to be three limitations to using GPS for vehicle guidance. The first is that GPS guidance systems cannot be used in microwave-shielded areas. Also, GPS cannot promise consistent positioning accuracy in the range of centimeters for a variety of field conditions (e.g., presence of buildings, trees or steeply rolling terrain, and interruption in satellite or differential correction signals). The second limitation is the inherent time delay (data latency) required for signal processing to determine locations that might present control system challenges at higher field speeds. The third is the high cost for agricultural application (although there is a consistent trend of cost reduction with widespread use). However, with the anticipated technology developments, these limitations will undoubtedly be overcome, thereby making GPS a choice candidate for incorporation into vehicle guidance systems.

Stoll and Kutzbach[41] studied the use of the RTK GPS as the only positioning sensor for the automatic steering system of self-propelled forage harvesters. They found that the standard deviation of steering was less than 100 mm under all conditions. Standard deviation of lateral offset (error) along straight-line paths ranged from 25 to 69 mm depending upon the travel speed.

Kise et al.[42,43] studied the use of an RTK GPS guidance system for control of a tractor as an autonomous vehicle traveling along a curved path. Test results for following a sinusoidal path with a 2.5-m amplitude and 30-m wavelength at 6.5 km/h showed a 6-cm RMS error with a 13-cm maximum error. To compensate for GPS positioning error associated with machinery attitude, researchers at Hokkaido University integrated an inertial measurement unit (IMU) with an RTK GPS to provide more accurate navigation information. This integrated navigation system could guide agricultural machinery performing all field operations, including planting, cultivating and spraying, at a travel speed of up to 3 m/s, with a tracking error of less than 5 cm on both straight and curved paths.

Ehsani et al.[44] evaluated the dynamic accuracy of several low-cost GPS receivers with the position information from an RTK GPS as reference. They found that these receivers had an average absolute cross-track error of around 1 m when traveling in a straight line. GPS cannot be effectively used for positioning in citrus applications since the vehicle frequently moves under the tree canopy, which blocks the satellite signals to the GPS receiver. Moreover, a system using GPS for guidance requires that a predetermined path be given for the vehicle to follow. Consequently, significant time must be spent in mapping its path.

Nagasaka et al.[19] used an RTK GPS for positioning, and fiber optic gyroscope (FOG) sensors to maintain vehicle inclination, for an automated six-row rice transplanter (Figure 4). Root-mean-square deviation from the desired straight path after correcting for the yaw angle offset was approximately 55 mm at a speed of 0.7 m/s. The maximum deviation from the desired path was less than 12 cm.

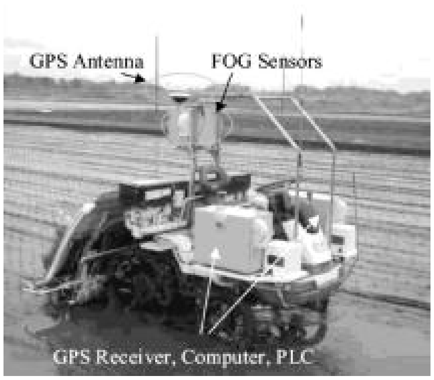


Figure 4 Automated rice transplanter [19]

3.3 Dead-reckoning sensors

Dead-reckoning sensors are inexpensive, reliable sensors for short-distance mobile robots, using a simple mathematical procedure for determining the present location of a vehicle by advancing a previous position through a known course and velocity information over a given length of time. The simplest form of dead reckoning is referred to as odometry. However, odometry is the integration of incremental motion information over time, which inevitably leads to the unbounded accumulation of errors. Specifically, orientation errors will cause large lateral position errors, which increase proportionally with the distance traveled by the robot. Despite these limitations, researchers use odometry as an important part of robot navigation systems[45,46].

Doppler sensors use the principle based on the Doppler shift in frequency observed when radiated energy reflects off a surface that is moving relative to the emitter. This type of sensor can decrease some of the errors arising from wheel slippage, tread wear, and/or improper tire inflation. Imou et al.[18] developed an autonomous tractor using an ultrasonic Doppler speed sensor and gyroscope. The results showed that the maximum lateral displacement from the reference line was less than 10 cm at a speed of 4 steps from 0.7 to 1.8 m/s on 50-m straight driving tests.

Imou et al. [47,48] developed a new ultrasonic Doppler sensor to achieve high accuracy when measuring the speeds of both forward and reverse motions including low-speed motions.

3.4 Laser-based sensors

Laser-based sensors have a relatively longer range and higher resolution. The guidance systems need three or more reflectors (landmarks) around the work field. The time at which the laser beam is detected is communicated to the guidance system, which uses triangulation to define the location of the vehicle. The system is insensitive to environmental conditions, e.g., strong light change for machine vision and microwave shadowing for GPS, which will make the system inoperable. However, laser-based sensor systems have two drawbacks. They do not work well if the position is changed for any of the artificial landmarks. If natural landmarks are used in the navigation process, map updating is necessary in order to register the landmarks in the map building operation. The second problem is noisy laser measurements when the vehicle is traveling on uneven ground.

Holmqvist [49] used a laser-optic navigation system for a vehicle moving at a speed of 2 m/s. With an average distance to the reflectors of 50 m, the absolute position error will typically be about 5 cm in each of the X, Y and Z directions. Ahamed et al. [50] used laser radar for developing a positioning method using reflectors for infield road navigation. They tested differently shaped reflectors to determine the accuracy in positioning. Junya et al. [51] used a single-laser distance sensor for vehicle navigation experiments, in which the vehicle repeated stop-and-go driving, stopping every 1 m for a distance of 20 m. The calculated RMS localization error in stopping was about 6 mm in the traveling direction and about 12 mm in the transverse direction.

Because the tree canopy frequently blocks the satellite microwaves to the GPS receiver, laser-based sensors are widely applied in orchards. Barawid et al. [52] developed an automatic guidance system for navigating between tree rows. Their research used a 56-kW agricultural tractor, 2D laser scanner, RTK GPS and FOG. The results showed an accuracy of 11 cm lateral error and 1.5° heading error. Subramanian[14] developed an autonomous guidance system for citrus grove navigation based on machine vision and laser radar. An average error of 2.8 cm using machine vision guidance and 2.5 cm using radar guidance was observed during vehicle testing on a curved path at a speed of 3.1 m/s.

Tofael [53] developed a complex autonomous tractor system with a laser rangefinder, RTK GPS and gyroscope. The results of field experiments using the laser rangefinder showed a lateral error of less than 2 cm and a heading error of less than 1°. The accuracy was very high.

3.5 Inertial sensors

Inertial sensors take measurements of the internal state of the vehicle. A major advantage of inertial sensors is that they are packaged and sealed from the environment, which makes them potentially robust under harsh environmental conditions. The most common types of inertial sensors are accelerometers and gyroscopes. Accelerometers measure acceleration relative to an inertial reference frame. This includes gravitational and rotational acceleration as well as linear acceleration. Gyroscopes measure the rate of rotation independent of the coordinate frame. They can also provide 3D position information and have the potential to detect wheel slippage. Unfortunately, these types of sensors are prone to positional drift [54].

Inertial sensors have been used in a number of vehicle applications[19,55,56]. The most common application is in the use of a heading gyro (e.g., Imou et al. [18]; Barawid et al. [52]; Ishida et al. [57]).

Inertial sensors are mostly used in combination with GPS or machine vision. Zhang and Reid[9] presented an on-field navigation system with a vision sensor, FOG and RTK GPS. The results indicated that the multiple sensor based agricultural navigation system was capable of guiding a tractor between crop rows and showed that the inertial sensor was a good assistant function.

Noguchi et al. [21] developed an agricultural navigation system consisting of an RTK GPS and an inertial measurement unit. Experiments conducted in a soybean field for tilling, planting, cultivating and spraying demonstrated that the accuracy of the vehicle surpassed that of skilled farmer operation. The lateral error of the guided vehicle was less than 5 cm.

3.6 Geomagnetic direction sensor (GDS)

A geomagnetic direction sensor (GDS) is a magnetometer that senses the earth's magnetic field. It can be used as a heading sensor similar to an electronic compass[6]. The GDS is generally used to supplement other sensors.

Noguchi et al.[58] used a GDS to provide heading information to a tillage robot. Benson et al. [11] used GPS with GDS for vehicle guidance along straight directional lines. One limitation of GDS sensors is the influence of external electromagnetic interference from the outside environment, such as from a nearby set of high-tension electrical wires or the vehicle heater/air conditioner fan. However, by controlling these error sources, they were able to combine GDS with a medium-accuracy GPS system (20 cm) and track a straight line with an average error of less than 1 cm. The maximum overshoot for a 3-m step response was 12%, compared to 50% for GPS alone.

The feasibility of correlating GDS with sensor applications for agricultural guidance systems has been researched. Harper and Mckerrow[59] used a frequency-modulated ultrasonic sensor to detect plants, setting up a plant database with a return signal containing information about the geometric structure of the plants to improve navigation. Yekutieli and Pegna [60] used a sensing arm to detect plants in the path for guidance in a vineyard.

However, using an arm would require that citrus groves be even with continuous canopy. There are also concerns about damaging the tree branches. Ultrasonic sensors are used for guidance in greenhouses, but they require that the target be perpendicular to the sensor for the ultrasonic waves to be reflected back properly (Subramanian et al. [14]). Dead reckoning is also widely used in combination with other sensors for autonomous vehicles (e.g., Morimoto et al. [61]).

4 Computational methods

A computational method is mainly to detect image features by image processing or deal with sensor data fusion successfully for providing with basic information for agricultural vehicle autonomous guidance system. Therefore, the method choice and improvement is very important.

4.1 Hough transform

The Hough transform technique can be used to isolate the features of a particular shape within an image. The transform was originally concerned with the identification of lines in the image, but later it was extended to identifying the position of arbitrary shapes, most commonly circles or ellipses. The Hough transform as it is universally used today was developed in 1972 by Richard Duda and Peter Hart, who called it a "generalized Hough transform" after the related 1962 patent of Paul V.C. Hough. The main advantage of using a Hough transform is that it is quite robust even if a group of points varies to some extent, and seeking a straight line is still possible. The disadvantage is that in order to plot curves (i.e., sinusoids) for every observation point in Cartesian image space to $r–\theta$ in the polar Hough parameter space, the load of computational complexity is large. As most crops are cultivated in rows, there are a number of publications on deriving guidance signals from plant structures using the Hough transform[15,26,27,52,56,62,63].

A stereovision-based crop-row detection method for tractor automated guidance[32] used a stereovision-based agricultural machinery guidance system. The algorithm consists of functions of stereo-image processing, elevation map creation and navigation point determination for crop row detection. The research also dealt with crop row detection for autonomous tractor guidance.

Åstrand et al.[15] modeled a plant row using a rectangular box instead of a line. The width of the box is equal to the average width of the plants and the length of the box is “unlimited” as it fills the whole image. The rectangular box can be described by a set of parallel adjacent lines, which appear in the image as a set of lines that intersect at a virtual point outside the image, as shown in Figure 5.

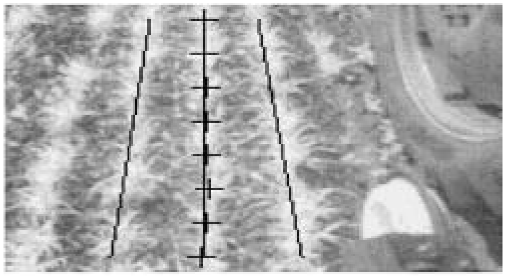
Figure 5 Rectangular box substitutes for a line [15]

4.2 Kalman filter

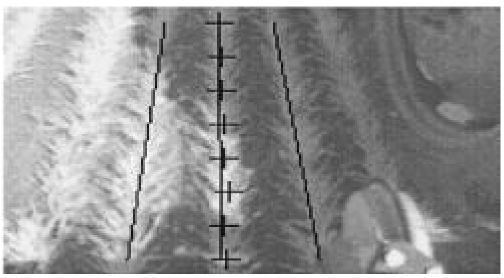
The Kalman filter[64] provides a sound theoretical framework for multi-sensor data fusion. The approach depends upon tracking the position of the vehicle or the state of the system at all times. Kalman filter models are often applied in GPS receivers to provide position estimates from raw GPS signals. In a highly dynamic system that has the potential for significant acceleration, it is necessary to integrate GPS with an Inertial Navigation System (INS) using Kalman filters. Literature on the integration of INS and/or other sensors with GPS is abundant[19,38,39,65-68]. These integrated systems can improve the positioning accuracy, and more importantly, can provide reliable short-term positioning information if the GPS signal is lost.

Han et al.[25] applied Kalman filtering to raw DGPS measurement data and effectively removed the DGPS noise and reduced the root-mean-squared (RMS) positioning error. The maximum cross-tracking error was reduced from 9.83 to 2.76 m and the root-mean-squared error was reduced from 0.58 to 0.56 m.

Hague and Tillett[28] provided a method in which image processing was combined with a bandpass filter and extended Kalman filter. The method does not rely upon segmentation of the plant background to reduce the brightness or color influence. Results are shown in Figure 6.



a. Uniform lighting conditions



b. With deep shadows

Fig.6 Row location[28]

A new sigma-point Kalman filter was proposed and used to improve the Kalman filter[69]. Zhang et al.[70] compared both filters through simulation and found that the sigma-point Kalman filter was more numerically robust and computationally efficient.

4.3 Other methods

Søgaard and Olsen[7] proposed a method based on machine vision for detection and localization of crop rows distinguished by using the generalized Hough transformation method (as shown in Figure 7). The method divided the grayscale image into horizontal strips and computed the center of gravity, by vector, as a substitute for the segmentation step to reduce the computational burden on the image processing.

Han et al. [25] used three methods to obtain a guidance directrix, which applied a *k*-means clustering algorithm for row segmentation, a moment algorithm for row detection, and a cost function for guidance line selection. The soybean field results showed an average RMS offset error of 1.0 cm from 30 images. The corn field results showed an average RMS offset error of 2.4 cm from 15 images.

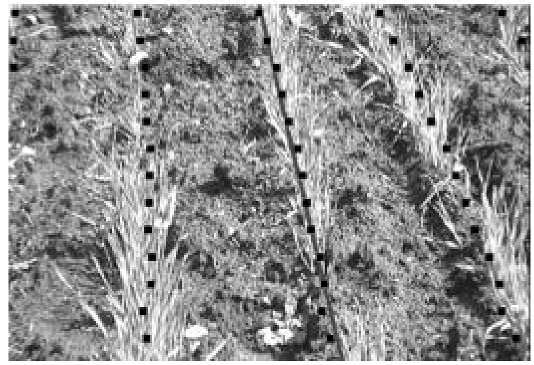


Figure 7 Middle line is the guiding row line [7]

5 Navigation planners

Navigation planner plays an important role for agricultural vehicle autonomous control, which transforms the position deviation (heading, position or state) of the vehicle or device into the steering angle. Besides including tracking methods, the navigation planning must consider the sensor information and vehicle motion to guidance in the desirable course.

5.1 Tracking methods

Navigation planning uses four methods: position tracking, line tracking, map tracking and obstacle avoidance. Most guidance system operations follow some nominal trajectory or directrix line. The method usually uses local information including crop rows, swath edges, and tilled/untilled boundaries. However, if the tracking signal weakens or vanishes, the operation fails. Map tracking is often used in GPS systems, but it is a labor- and time-intensive method.

5.2 Vehicle motion models

1) Dead reckoning

Dead reckoning is reliable for short-distance traveling (two positions) on a smooth concrete road. Since motion information is integrated in order to obtain the position of the vehicle, there is a risk of error accumulation leading to positional drift if the sensor produces even a slight bias. On agricultural vehicles, dead-reckoning sensors can be as simple as wheel encoders, which measure the rotation of the vehicle or equipment wheels. Freeland et al.[71]

experimented with a low-cost electronic compass used together with wheel encoders to provide dead-reckoning position information. Dead reckoning is widely used in combination with other sensors for autonomous vehicles. Nagasaka et al.[19] and Kodagoda et al.[72] used rotary encoders. Garacía-Pérez et al.[73] used odometers and a proximity capacitive sensor.

2) Kinematic model

Kinematic models are very simple and have been used by researchers to describe the lateral error relative to a nominal trajectory without taking into account vehicle dynamics[10,11,13,21]. Some of the research showed very good accuracy of less than 5 cm not only on a straight line but also on a curved path as soon as the vehicle satisfied the pure rolling constrains. Unfortunately, pure rolling constraints are almost impossible to satisfy during agricultural tasks due to sliding, deformed tires or change in wheel-ground contact conditions, which degrade the performance and stability of automatic guidance. Some literature is related to improved kinematic models that can adapt to the sliding influence and promise guidance accuracy (e.g., Lenain et al.[74,75]; Fang et al.[76]). The sliding effects have been taken into account for trajectory tracking control of agricultural vehicles and three variables characterizing the sliding effects were introduced into the kinematic model based on geometric and velocity constraints. An ideal refined kinematic model was obtained in which sliding effects appeared as additive unknown parameters using linearized approximation.

3) Dynamic model

Dynamic models are fairly complex for agricultural vehicle navigation, since describing all vehicle features (e.g., inertia, sliding, springing) leads to very large, intricate models. In particular, most of the parameter values (mass, wheel-ground contact conditions, tire and wheel deformation) are difficult to obtain even based on experimental identification. However, agricultural vehicle tasks involve mostly dynamic processing and researchers are interested in investigating this[77-79].

4) Sensor fusion

The principle of sensor fusion is to combine information from various sensing sources (e.g., GPS and machine vision, GPS and GDS) since an individual sensing technology cannot satisfy vehicle automation navigation operation for all models and all methods of use in different environments. The appropriate sensor will function at the appropriate field status during operation. Nevertheless, even under a given field operation, the availability of data from multiple sensors provides the opportunity for better data integration to provide superior results compared to those using an individual sensor. Sensor fusion technology is becoming increasingly popular for agricultural navigation[12,20,25].

Zhang et al.[9] developed an on-field navigation system using a vision sensor, FOG and RTK GPS. Figure 8 shows the comparison results. Garacía-Pérez et al.[73] developed a hybrid agent for behavior architecture adapted to agricultural navigation. The farming vehicle was equipped with several positioning sensors (DGPS, digital compass and dead-reckoning system) and safety sensors (laser rangefinder, bumper, inclinometers, emergency stops) as well as an on-board processor, wireless communication system (WLAN) and electrohydraulic actuators. Sensor-fusion algorithms were proposed to overcome the absence of GPS signals so as to obtain continuous and precise positioning.

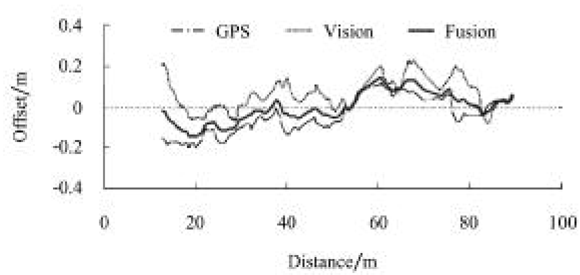


Figure 8 Comparison of navigation accuracy in vehicle offset from the desired path using sensor fusion, vision only, and GPS-FOG only based navigation controls [9]

5) Neural steer model

Noguchi and Terao [20] designed a neural network (NN) vehicle controller in which the motion of the mobile agricultural robot was specified as a nonlinear system with high learning ability. This NN model was applied to navigation on an asphalt surface, with an accuracy of 0.08 m in the offset. Noguchi et al. [58] used an NN model to correct the geomagnetic direction sensor for the inclination of the vehicle. A field test was conducted on a square path (40-m sides) in a meadow. The maximum directional angle error was 14° using the conventional method, but only 1° using the NN. Zhu et al. [80] designed an NN vehicle model for estimating vehicle behavior on sloping terrain. Bernoulli's lemniscate was employed to acquire training pairs. Genetic algorithms and back propagation algorithms were used to train the NN vehicle model. The tractor was successfully guided along a predetermined path with mean and standard lateral deviation of 5 and 6.7 mm, respectively. Ryerson and Zhang[81] chose genetic algorithms to plan the optimal path for a guided vehicle to avoid known obstacles.

6 Steering controller

A good control system is necessary irrespective of the guidance sensor. The controller translates sensor position deviation signals into a voltage signal that is used to open a valve forcing the hydraulic ram in the steering circuit to change the steering angle of the front or rear axle, or, in the case of side shifting the equipment, an additional ram to adjust the position of the equipment relative to the tractor or the row of plants.

Agricultural vehicles often work on different types of terrain, even and uneven, or changing and unpredictable terrain ranging from asphalt to spongy topsoil in the field. In the case of automatic or autonomous navigation, steering controllers should be able to provide appropriate steering action in response to the variation in equipment operation state, traveling speed, tire cornering stiffness, ground conditions, and many other parameters influencing steering dynamics. Consequently, steering controller design for agricultural vehicles is a difficult challenge.

Most modern agricultural vehicles employ some form of hydraulic steering system, and recent developments in automatic steering controllers include advanced modifications to the existing hydraulic system considering vehicle dynamics, such as terrain conditions and vehicle status (speed and/or acceleration). Various steering controllers, including PID, feed-forward PID (FPID), and fuzzy logic (FL) controllers, have been developed and implemented in guidance systems [9, 82,83]. O'Connor et al.[13] used a steering controller based on a set of linear motion equations. Inoue et al. [84] developed an adaptive steering controller that corrects the steering system delay. Cho and Lee[85] used a fuzzy logic controller for the autonomous operation of an orchard speed sprayer. Kise et al.[43] developed an optimal steering controller and obtained good curved-path guidance results. Zhang et al.[10] put forward a kinematic model in which the steering linkage geometry provided the gain between the hydraulic actuator and the front wheels. The system model was used to close the steering control loop based on the feedback signal from the hydraulic steering actuator rather than from the front wheels. Lenain et al.[75] considered agricultural vehicle sliding and pseudo-sliding on slippery ground and used predictive model control to preserve accuracy.

An actuator, combined with the vehicle status, was used to convert the control signal from a feedback controller to the appropriate mechanical adjustment in steering angle to provide the position of the vehicle.

7 Discussion

Since the time when the first 'driverless tractor' prototype was created 50 years ago (Morgan 1958), research into automatic guidance has steadily progressed, particularly in the case of guidance system technologies, which have improved remarkably in the last two decades. However, with the exception of GPS receivers, vision sensors, laser rangers, gyroscopes and GDS, the commercialization of prototype agricultural guidance systems is very low. Various reasons are behind the absence of funds for developing these prototypes into commercial products. Some cases have fallen into disuse as society has developed. For example, new technology or production causes the prototype market to devalue, and performance standards for environmental protection and implementing tractors are changing. Nevertheless, some general conclusions can be drawn regarding the failure of many prototype 'service robots' to reach commercial viability.

The environmental and performance requirements for agricultural vehicle guidance operation are extremely strict (see Section 2). In addition to this barrier (a more difficult consideration than other guidance applications), there are others barriers that have not yet been resolved from many years ago. Hague et al.[24] concluded that dead-reckoning sensors lead to the accumulation of errors resulting in positional drift; laser or radar and image based artificial landmark positioning systems are a direct function of positioning, and not prone to accumulating drift errors, but the beacons take time to set up and may result in ambiguous and unreliable results due to false detection and failure to detect obscured beacons. The popular machine vision and GPS also have their respective advantages and disadvantages. Machine vision is an inexpensive and passive sensor, which has some excellent computer algorithms to support and advance successful research[14,25]. However, it also has difficulty dealing with changing light conditions, shadows, direct sunlight and other difficulties with extracting guidelines from the images captured in the working environment. Although most problems can be solved with electronic shutters, automatic diaphragms, color differences and the right position and adjustment of the camera, a row of plants or a furrow is needed to guide the vehicle using image processing, and tasks such as spraying or fertilizing uncultivated fields need another strategy. GPS is different than machine vision, as it is not affected by environmental variations, and real-time kinematic (RTK) GPS can provide better accuracy. Nevertheless, GPS sensor accuracy depends on the position of the satellites. In urban environments, especially in narrow streets (urban canyons), buildings can occult the microwaves from satellites. Moreover, a system using GPS for guidance requires that a predetermined path be given for the vehicle to follow. Secondly, a kinematic GPS is very expensive. GPS guidance systems pose a problem in terms of positioning the antenna on the roof of the agricultural vehicle with the equipment working at the ground level. This means that on sloping ground and with changing soil conditions, deviations can occur between the virtual guideline and the path described by the equipment. Solving this problem requires attitude measurement.

With the advent of computer vision and GPS and their declining prices, it seems inevitable that these two technologies will be ‘fused’ together or one of them will be ‘fused’ with another technology, such as gyroscopy[19,61], GDC[11] or laser radar[14], to realize autonomous vehicles in agriculture, allowing real-time image processing with a digital controller on a simple PC, precision positioning with an RTK DGPS system or heading computation with a traditional gyroscope.

However, if the guidance system for agriculture is commercialized, the following product research will be needed as single technologies mature. An integrated consideration may be better.

1) Evaluation of economic feasibility. Electronics, computers, sensors and attachments are declining in price, mostly because high commercial demand enabled their manufacture at great economies of scale; however, the cost of designing and producing the special-purpose parts for agricultural guidance systems will increase markedly. An evaluation of economic feasibility is necessary to determine the market value and understand the difference compared with old conventional systems.

2) Improvement of robustness in versatility and dependability of mechanical technology. The agricultural machine operates in a harsher environment (often in paddy fields), but its operating time adaptability is stronger than other machines for harvesting, sowing and spraying and the operating times are usually pivotally related to benefit the farmers. Hence, such machines should be sufficiently robust to work effectively under varying conditions. Today’s technologies have not always proven capable of delivering this performance.

3) Addition of safety to avoid the risk of damage resulting from the use of such machines. Although the safety standard is different from countries, the use of automated machine will substantially increase a user’s legal liability. If the users utilize the insurance against all damages resulting from the uses of such machines, the cost may be very expensive. Thereby, it should be necessary to consider the safety of such machines based on different safety standard.

4) Provision of service system. A sophisticated machine that is broken cannot do a better job than a primitive machine. As machines become more

complicated, the skills required for their operation and maintenance increase in proportion. For agricultural application, the service system will be more important than in a factory environment, because there are very few, if any, technicians who will have the expertise or equipment for repairs and maintenance.

With the emergence of new technologies in the industry, research into their application to agricultural vehicle guidance systems will contribute to the realization of autonomous agricultural vehicles or robots in the future. For example, omnidirectional vision sensors[86] have become increasingly attractive for autonomous navigation systems. The camera and mirror are mounted at the top of the mobile robot's platform. Images captured by the sensor are an orthographic projection of the ground plane. The images (obtained without rotating the robot) are a 360° view of the environment and therefore are not sensitive to wheel slippage or small vibrations. This low-cost sensing device provides enough information for our navigation system. Although it is not easy to obtain distance estimations from an omnidirectional image due to the shape of the mirror, the apparent angles of objects around the robot are relatively accurate and easy to derive from the image[87,88]. We proposed this system as a potential substitute for the GPS function for localization using landmarks in the working environment.

8 Conclusions

This paper provides a brief review of the research on guidance system technologies in agricultural vehicles over the past 20 years. Although the research developments are abundant, there are some shortcomings (e.g., low robustness of versatility and dependability of technologies) that are delaying the improvements required for commercialization of the guidance systems. It can be concluded that either GPS and machine vision technologies will be 'fused' together or one of them will be 'fused' with another technology (e.g., laser radar) as the trend development for agricultural vehicle guidance systems. The application of new popular robotic technologies for agricultural guidance systems will augment the realization of agricultural vehicle automation in the future.

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Developing a modeling tool for flow profiling in irrigation distribution networks

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Abstract: Efforts are underway to rehabilitate the irrigation districts, such as in the Rio Grande Basin in Texas. Water distribution network models are needed to help prioritize and analyze various rehabilitation options, as well as to scientifically quantify irrigation water demands, usages, and losses, and to help manage gate automation. However, commercially available software packages were limited in applications due to their high cost and operational difficulty. This study aims to develop a modeling tool for modeling the water flow profile in irrigation distribution networks. The goal of developing the modeling tool was to make the modeling process simple, fast, reliable and accurate. On the basis of methodological study, the modeling tool has been developed for branching canal networks with the assumption of steady gradually varied flow. The flow profile calculation of the tool was verified from a single channel with 1% root mean squared error compared to the benchmark calculation and a branching network with 5% to 12% relative errors compared to check point measurement along the network. The developed modeling tool will be able to play an important role in water quantification for planning, analysis and development for modernization of irrigation systems.

Keywords: irrigation distribution network, modeling tool, flow profiling

DOI: 10.3965/j.issn.1934-6344.2009.03.017-026

Citation: Yanbo Huang, Guy Fipps. Developing a modeling tool for flow profiling in irrigation distribution networks. Int J Agric & Biol Eng, 2009; 2(3): 17－26.

1 Introduction

Irrigation distribution networks are used extensively for agricultural water supply. Irrigation districts deliver water to farms through the channels and pipelines. Efforts are underway to rehabilitate the irrigation districts. Quantitative evaluation tools are needed to help prioritize and analyze various rehabilitation options, as well as to scientifically quantify irrigation water demands, usages, and losses, and to help manage gate automation. There has been much research in developing computer models and software packages for water resources planning and management through the past three decades[1]. Models and software packages are commercially or research available for flow modeling and gate automation of irrigation channels. Examples are: SOBEK (Delft Hydraulics, Delft, Netherlands), an integrated 1D/2D modeling program for water management, design, planning and policy making in river, rural and urban systems (http://www.sobek.nl/prod/index.html); CanalCAD (Laboratoire d'Hydraulique de France, Grenoble, France; Parrish Engineering, Beaverton, Oregon, USA), a hydrodynamic simulator of both steady and unsteady flow in canal systems with manual or automatic gates (http://www.iihr.uiowa.edu/projects/

Received date: 2009-02-19 **Accepted date:** 2009-09-10

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canalcad/index.html); Mike 11 (Danish Hydraulic Institute, Hørsholm, Denmark), a versatile and modular engineering software tool for modeling conditions in rivers, lakes/reservoirs, irrigation canals and other inland water systems (http://www.dhisoftware.com/mike11); SIC (Cemagref, Antony Cedex, France), a simulation model for canal automation design (http://canari. montpellier.cemagref.fr/papers/sic30.pdf); HEC-RAS (IWR, US Army Corps of Engineers, Davis, California, USA), a software package that allows one-dimensional steady and unsteady flow calculations in natural channels (http://www.hec.usace.army.mil/software/hec-ras); and CanalMan (Utah State University, Logan, Utah, USA) a model that performs hydraulic simulations of unsteady flow in branching canal networks (http://www. engineering.usu.edu/bie/software/canalman.php). These models or software packages are for general use and either expensive, such as SOBEK and CanalCAD or are difficult to be customized for applications under specific conditions even free downloadable, such as HEC-RAS and CanalMan.

Models have been evaluated for irrigation systems. Wallender[2] has done model simulation for both a single furrow as well as on a field-wide basis. Model simulations were evaluated to determine the importance to irrigation performance of each spatially-varying model input. Esfandiari and Maheshwari[3] studied four furrow irrigation models, referred to as the Ross, Walker, Strelkoff and Elliott models for their prediction of advance and recession times and runoff, and for their computational time per simulation run and volume balance error under three field conditions in south-east Australia. Hidalgo et al.[4] developed a procedure for calibrating on-demand irrigation network models. This procedure compared a new objective function with two more commonly used objective functions. This procedure was applied to an on-demand irrigation network located in Tarazona de La Mancha (Albacete, Spain) where flow and pressure at hydrant level was measured. Islam et al.[5] presented a hydraulic simulation model developed for steady and unsteady flow simulation in irrigation canal network. The model uses the implicit four-point Preissmann scheme for discretization of the Saint-Venant equations and solves the resulting equations using the sparse matrix solution technique. The model is applicable for simulating flow in a series of linearly connected reaches, and branched as well as looped canal networks. In general, unsteady gradually varied flow (USGVF) can be described by the Saint-Venant equations[6]. These equations are simultaneous partial differential equations with a number of boundary conditions. However, in practice use of a unsteady canal model requires serious investments of time and personnel[7]. As a special case of USGFV, steady gradually varied flow (SGVF) can be described by a single ordinary differential equation[6], which is much more easily implemented than the Saint-Venant equations. In many cases the description of SGVF is very useful and effective and the USGVF could be simplified to cascaded SGVFs in solving problems in flow computation and analysis.

The objective of the study was to develop a modeling tool based on the description of SGVF for modeling the water flow profile in irrigation distribution networks in the Rio Grande Basin in Texas and other similar areas. The developed modeling tool will make the modeling process simple, fast, reliable and accurate.

2 Study area

Irrigated lands in different areas have different characteristics. This study will focus on the irrigated areas with the following characteristics:

- The waterways are shallow and have small hydraulic gradients. In other words, the channel bottom slope is small and the water flows mildly from upstream to downstream with gravity and sufficient head pressure;
- The distribution networks are dendritical, i.e. the routes of the networks are branched but not looped.
- The networks are open channels

In the Lower Rio Grande Valley in Texas (Figure 1), the project area, the elevations range from sea level in the east to about 200 m in the northwest, but are mainly less than 100 m. Much of the area is nearly level. Drainage ways are shallow and have low gradients. The canals and pipelines in the distribution networks have small hydraulic gradients with few relief pumps. The objects of this study will be irrigation canals.

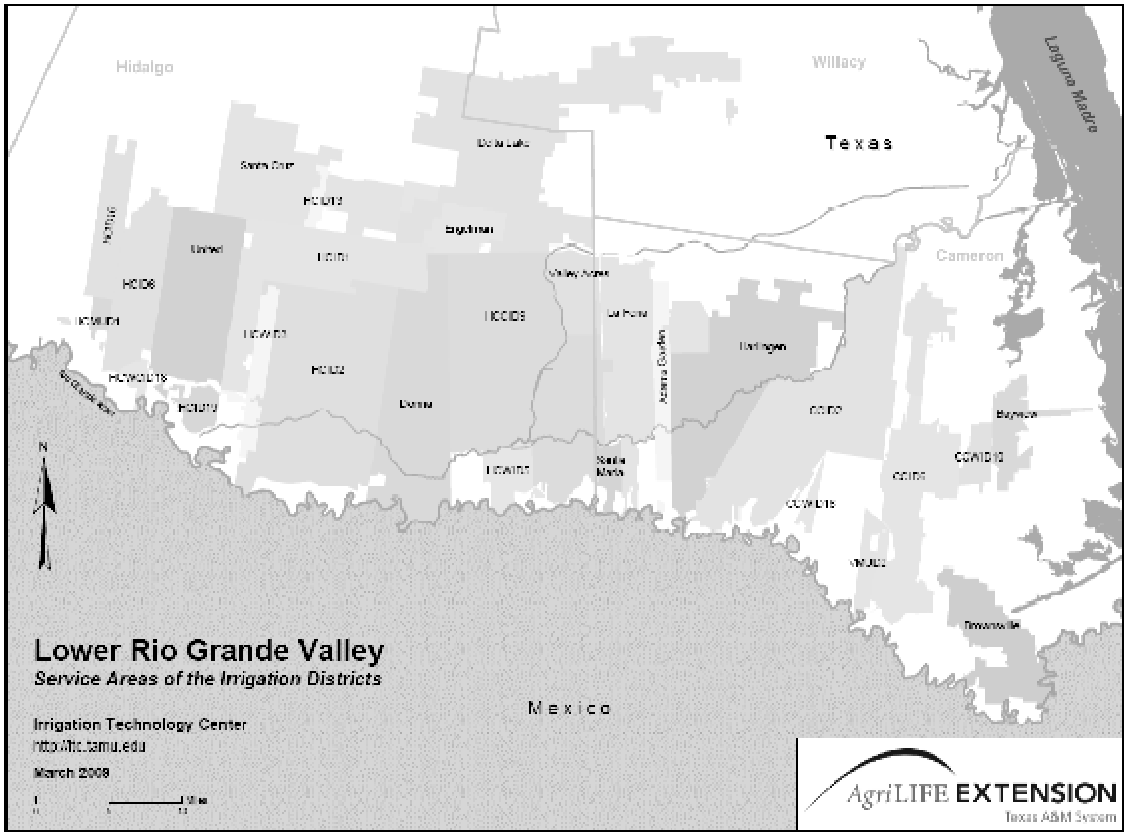

Figure 1 Service areas of the irrigation districts in Lower Rio Grande Valley of Texas

3 Computing methods

In the open-channels (canals) of irrigation networks, water flows are typically categorized as:

1) Steady uniform flow (SUF); 2) Steady gradually varied flow (SGVF); and 3) Unsteady gradually varied flow (USGVF).

The SGVF can be computed and analyzed by observing the conservation of mass and energy with an ordinary differential equation[6]. Further, the USGVF can be computed and analyzed using the Saint-Venant equations observing the conservation of mass and momentum[6]. It can be derived mathematically that the SGVF is a special case of the USGVF. The Saint-Venant equations are partial differential, so the implementation of the computation is much more difficult. In practice the SGVF is very useful and effective in solving a lot of problems in flow computation and analysis. With the fundamental equation the solutions can be cascaded along a canal channel and the layout of a distribution network under different initial and boundary hydraulic conditions.

Non-uniform flow is the prevailing flow conditions in irrigation systems. For the area the irrigation channels are shallow and have small hydraulic gradients such as the Rio Grande Basin in Texas the SGVF is the dominate flow type unless some transient processes typically happened around gate structures would result in the USGVF flow condition. Therefore, the computation of the SGVF profiles in irrigation distribution networks is the technique needed in developing the modeling tool.

3.1 SGVF flow profile computation

The computation of the SGVF profiles basically solves the governing ordinary differential equation. The main objective of the computation was to determine the shape of the flow profile. Broadly three methods of the computation were classified as[6]: the graphical-integration method, the direct-integration method, and the step method.

The graphical-integration procedure is straightforward and easy to follow but it may become very laborious when applied to actual problems. Because the differential equation of the SGVF cannot be expressed explicitly in terms of y for all types of channel cross sections, a direct and exact integration of the equation is practically impossible; hence, so far this method has been developed either to solve the equation for a few special cases or to introduce assumptions that make the equation amenable to mathematical integration[6]. Basically a step method is to divide a channel into short reaches and carry the computation step by step from one end of the reach to the other. There are a great variety of step methods. Some appear superior to others in certain respects, but no one has been found to be the best in all applications.

This study gives a step method based on the need of flow profile computation for irrigation channels. This method divides a channel to small reaches. The length of the reaches cannot be too big because this may cause the iterative procedure to fail, and cannot be too small either because this should increase computational burden. With the divided reaches the computation starts from the downstream end of the channel for subcritical flow (from the upstream end for supercritical flow) by applying the Bernoulli equation to the reach:

$$y_u + a\,\frac{v_u^2}{2g} + S_o\Delta x = y_d + a\,\frac{v_d^2}{2g} + S_f\Delta x \qquad (1)$$

where v_u and v_d are the flow velocities at the upstream and downstream ends of the reach respectively; α is the velocity distribution coefficient which takes into account that in channel cross-section the distribution of velocity is not uniform; Δx is the length of the reach; S_o is the channel bottom slope.

The solution of the equation for subcritical flow will be water depth h and water level $z=y+\Delta z$ at the upstream end of the reach where Δz is the difference between the elevations at the upstream and downstream ends of the reach. Equation (1) can be reformed to solve the water depth at the upstream end of the reach:

$$y_u = y_d + a\,(\frac{v_d^2}{2g} - \frac{v_u^2}{2g}) - S_o\Delta x + S_f\Delta x \qquad (2)$$

and

$$S_f = \frac{n^2Q^2}{\bar{A}^2\bar{R}^{4/3}}$$
$$\bar{A} = \frac{A_u + A_d}{2} \qquad (3)$$
$$\bar{R} = \frac{R_u + R_d}{2}$$

where A_u and A_d are the channel cross section areas of the upstream and downstream ends respectively; R_u and R_d *are* the channel hydraulic radiuses of the upstream and downstream ends respectively.

With the solutions as the initial conditions the equation can be applied to the next reach and so on.

The computation at each reach is an iterative process. Given Q, n, S_o, and channel cross section parameter such as bottom width b and side slope s for a trapezoid cross section, at the beginning the upstream end water depth y_u *was* set to be the downstream end water depth y_d which was from the solution of the previous reach or the initial condition at the channel downstream end, i.e. y_u=y_d. With the initial y_u a new estimate of the unknown water depth using equations (2) and (3) was calculated as $\hat{y}_u$. Then, the initial water depth was compared with the estimated depth with $|\hat{y}_u - y_u| < e$ where e was a pre-set small number for stopping the iteration. If the stopping condition is met, the iteration will stop and $\hat{y}_u$ is the solution; otherwise set $y_u = \hat{y}_u$ and continue the iteration.

3.2 Branching network SGVF flow profiling

The algorithm above can be used to compute SGVF flow profiling in a canal channel or a distribution network by cascading the solutions step by step along the canal channel and the layout of a distribution network under different initial and boundary hydraulic conditions.

Branching irrigation distribution networks are dominated in the studied areas. This kind of networks typically consists of laterals, second-level laterals, and even third-level laterals along a main canal. The flow profile computation over a branching network starts by initializing discharge and water depth at the one end of the main canal. Then when the computation proceeds to a lateral, the computation needs to continue by initializing discharge and water depth at the one end of the lateral. When the computation proceeds to a second-level lateral, the computation needs to continue by initializing discharge and water depth at the one end of the second-level lateral. Keep on going like this until the farm turnouts are reached and the computations needs to recursively go back to the main canal. The same procedure follows when the second, third, … laterals are met. The computation will stop when it proceeds to the other end of the main canal. Figure 2 shows the flow chart of the procedure of subcritical SGVF profile computation over a branching irrigation network. This procedure can handle the branching irrigation networks in arbitrary layouts as long as they only have the first-level laterals. This procedure can be easily extended to the cases of arbitrary branching networks with second-level, third-level, and *n*-level laterals.

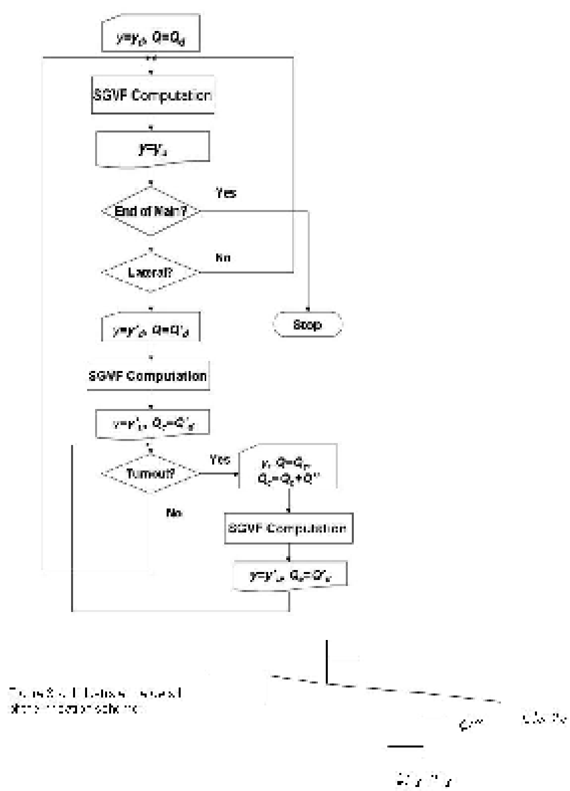

Figure 2 Flow chart of computation of subcritical SGVF profile over branch irrigation networks with first-level laterals

3.3 Gate calibration

Gate is the most popular structure for controlling water flow through irrigation channels. In general, four different flow regimes can occur at gate structures. Each of the four regimes has a standard equation to characterize the flow through the gate structure[9,10]:

1) Free orifice (FO): it is free gated flow

$$Q = C_{fo} L G_o \sqrt{2g(y_u - 0.5G_o)} \tag{4}$$

where L is the gate size; G_o is the gate opening; y_u is the water depth upstream of the gate structure; C_{fo} is the discharge coefficient of the FO flow.

2) Submerged orifice (SO): it is submerged gated flow

$$Q = C_{so} L y_d \sqrt{2g(y_u - y_d)} \tag{5}$$

where y_d is the water depth downstream of the gate structure; C_{so} is the discharge coefficient of the SO flow.

3) Free non-orifice (FN): it is free weir flow

$$Q = C_{nf} L \sqrt{y_u} \tag{6}$$

where C_{nf} is the discharge coefficient of the FN flow.

4) Submerged non-orifice (SN): it is submerged weir flow

$$Q = C_{sn} L y_d \sqrt{2g(y_u - y_d)} \tag{7}$$

where C_{sn} is the discharge coefficient of the SN flow.

In practice, although water flow can transit from one regime to the other, many canal gate structures and channel constrictions such as flumes operate mostly under a single flow regime.

To use any one of the equations (4), (5), (6), and (7) to characterize the water flow though a specific gate structure, the corresponding discharge coefficient, C_{fo}, C_{so}, C_{fn}, or C_{sn}, needs to be determined (calibrated). The calibration procedure is as follows[9]:

1) Conduct field survey around the concerned gate structure: gate dimensions and gate upstream and downstream channel hydraulic characteristics.

2) Determine the flow regime by experience or by some computation about water flow through the gate structure.

3) Find out the standard equation of a specific gate structure for the determined flow regime: equation (4), (5), (6), or (7).

4) Rearrange the equations (4), (6), and (7) in the following general form:

$$Qp(y_u, y_d, G_o, L) = Cq(y_u, y_d, G_o) \tag{8}$$

where C is C_{fo}, C_{fn}, or C_{sn}.

Equation (4) can be assumed in the form:

$$\log_{10}(C_{so})=a+b*\log_{10}(y_d/G_o) \tag{9}$$

where a and b are regression coefficients.

I. Based on the n sequential measurements of (Q_i, y_u^i, y_d^i, G_o^i) (i=1,2,…,n), calculate ($q_i(y_u^i, y_d^i, G_o^i)$, $Q_i p_i(y_u^i, y_d^i, G_o^i, L)$) for equation (8) or ($\log_{10}(y_d^i/G_o^i)$, $\log_{10}(C_{so}^i)$) for equation (9) (i=1,2,…,n).

II. Based on the calculation, the regression equation is formulated as:

$$p=\hat{C}q/Q \tag{10}$$

for FO, FN, or SN flow where $\hat{C}$ is the estimated value of C, or

$$\log_{10}(C_{so})=\hat{a}+\hat{b}*\log_{10}(y_d/G_o) \tag{11}$$

where $\hat{a}$ and $\hat{b}$ are the estimated values of a and b respectively.

III. The performance of the calibration can be evaluated by calculating the standard deviations of residuals.

4 Modeling tool prototyping

Using the method above the modeling tool was programmed and developed. In order to make the modeling process simple, fast, and accurate, three modules have been developed:

1) SGVF computation for a single canal channel

2) SGVF computation for branching canal networks

3) Flow computation through control sections

The third module is for computing the flow through gates, weirs, and flumes. The discharge and depth relationships were calibrated and saved for model implementation.

C++ programming language was chosen for prototyping the modeling tool. The programs were designed and developed using the principles of OOP (Object-Oriented Programming).

5 Model validation

The water flow profiles in a single irrigation canal channel and a branching network irrigation scheme were computed for model validation. As the benchmark, the data of the single irrigation canal channel were taken from Chow (1959)[6]. The computing results were compared with Chow's computation to validate the computation of this study.

The irrigation scheme is a real-world irrigation branching network (Figure 3), which spans about 1700 m and is located at an irrigation district Jamaica around an area that has similar characteristics as the Lower Rio Grande Valley of Texas. The data were measured and collected from the field survey and flow measurement. The computing results were verified with check point values along the irrigation system. In the scheme, the main canal goes through the points 1, 2, 3, 4, 5, 6, and 7. In the main canal at the upstream end is a sharp-crested weir (HS1). A siphon wall is in the middle (HS2). At the downstream end is another sharp-crested weir (HS5). Two laterals are from the main canal through two sluice gates: HS3 and HS4 respectively. HS3 was fully shut down during field survey and measurement. HS4 was open to allow water flow to go through the points 5a, 5b, 5c, 5d, 5e, 5f, 5g and 5h. HS 6 and HS7 are two sluice gates to the farm turnouts at 5f and 5h respectively.

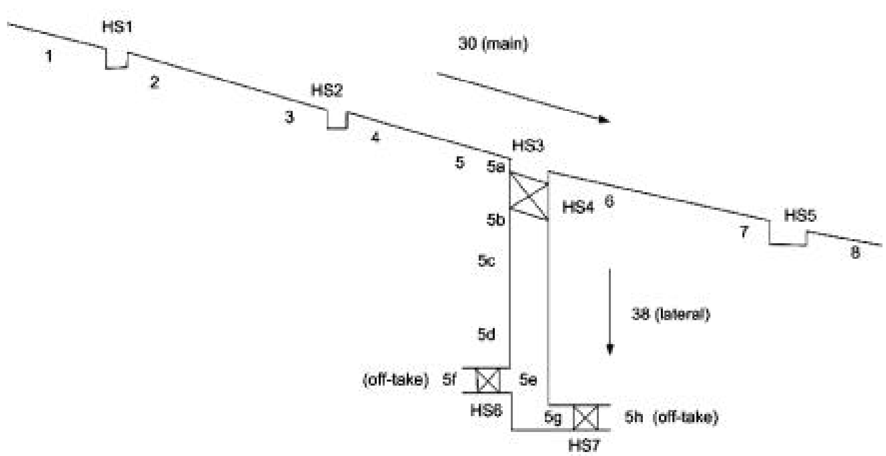

Figure 3 A branching network irrigation scheme

Before computing the water level profile, these sluice gates need to be calibrated. With the data collected during the field survey and flow measurement the results of the calibrations are shown in Table 1.

Table 1 Gate calibration in the branching network irrigation scheme.

Gate	Flow regime	Gate status	Gate flow equation
HS3	NA	Closed	NA
HS4	Free Weir Flow	Open	$Q = C_{nf} L y_u^{1.5}$ $C_{nfw} = C_{nf} / \sqrt{2g}$ $\hat{C}_{nfw}$ =0.0469
HS6	Submerged Orifice Flow	Open	$Q = C_{so} L y_d \sqrt{2g(y_u - y_d)}$ C_{so}=0.3148 $(y_d/G_o)^{-0.2917}$
HS7	Submerged Orifice Flow	Open	$Q = C_{so} L h_d \sqrt{2g(y_u - y_d)}$ C_{so}=0.609677$(y_d/G_o)^{-2.2873}$

With all of the data collected in field survey and flow measurement, and gate calibration equations, the modeling tool computed the water level profile over the branching network irrigation scheme automatically. A group of measured data was used to initialize model computation (from main and lateral downstream ends) and to verify the computation results at some check point through the network scheme. This group of data is listed Table 2.

Table 2 A group of measured data for model computation initialization and verification.

	Data	Usage
Head on HS5	0.22 m	Initial condition
Gate Opening at HS4	0.30 m	Boundary condition
Discharge over HS5	0.35 cms*	Initial condition
Gate Opening at HS6	0.37 m	Boundary condition
Discharge through HS6	0.01 cms	Initial condition
Gate Opening at HS7	0.58 m	Boundary condition
Discharge through HS7	0.03 cms	Initial condition
Depth upstream of HS7	0.255 m	Initial condition
Depth upstream to point 5	0.67 m	Verification
Head on HS1	0.21 m	Verification

Note: *cms – cubic meter per second.

6 Results and discussion

6.1 Single irrigation canal channel

Chow (1959) [6] gave an example of computing the subcritical water level profile in a trapezoid channel. This profile was created by a dam which backs up the water to a depth of 1.53 m immediately behind the dam. This channel carries a discharge of Q=11.33 cms with b= 6.10 m (channel bottom width), s=2 (channel side slope), S_o=0.0016, and n=0.025. The length of the profile is about 732 m.

Chow used two methods for the computation: the graphical-integration method and the direct step method. The computation of this study was compared with Chow's direct step computation. Table 3 shows this comparison. RMSE (Root Mean Squared Error) of this computation with Chow's computation is 0.011219 (1%), which indicates that the computation of this study is very close to what Chow computed. Figure 4 is the plot of the comparison of the computed water levels.

Table 3 Computed water level profiles of the trapezoid channel (1.53 m water depth behind the dam, Q=11.33 cms, b=6.10 m, s=2, S_o=0.0016, n=0.025, and length of the profile is 732 m)

x – distance to the channel downstream end /m	y – computed water level profile in this study /m	y' – computed water level profile by Chow (1959)[6] /m	$[(y-y')/y']^2$
0.00	1.52	1.52	0
47.09	1.54	1.53	3.92E-06
97.22	1.56	1.55	3.45E-05
148.86	1.59	1.57	9.32E-05
206.58	1.63	1.61	0.000129
270.38	1.67	1.65	0.000218
347.85	1.74	1.71	0.000256
396.46	1.79	1.76	0.000242
455.70	1.85	1.82	0.000225
493.68	1.90	1.87	0.000214
539.25	1.95	1.93	0.000159
575.70	2.00	1.97	0.000151
622.79	2.06	2.04	7.97E-05
663.80	2.12	2.10	5.22E-05
721.53	2.20	2.19	3.09E-05
		RMSE	0.011219(1%)

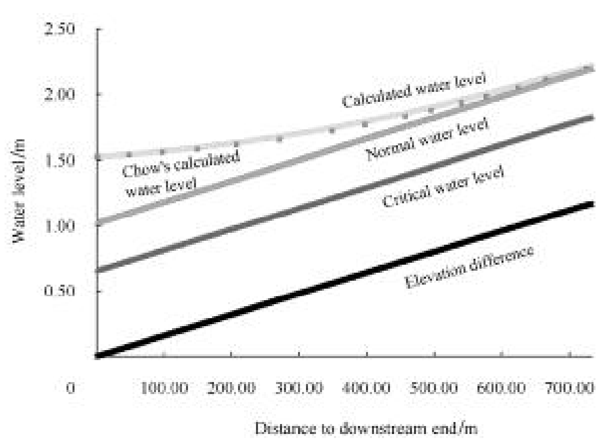

Figure 4 Plot of computed water level profiles of the trapezoid channel

6.2 Branching network irrigation scheme

All of the computing results are summarized in Table 4 compared with the measured data at check points. The following figures illustrate the numbers in the table.

Table 4 Modeling tool computation result summary

Location	Initial and computed discharge /cm • s^{-1}	Computed water depth /m	Measured water depth /m	Comment
Main downstream	0.35		0.22 m	Initial conditioned
Channel 6-7 (244 m)	0.35	0.49 m		
Channel 5e-5g (15 m)	0.03	0.23 m	0.26 m	Initial conditioned and the relative error between computed and measured water depth is 11.5%
Channel 5b-5e (122 m)	0.01	0.37 m		Initial condition
Channel 4-5 (244 m)	0.4	0.67 m	0.67 m	Based on the computation, the 0.67 m depth happened at about 6.1 m upstream point 5
Channel 2-3 (1,219 m)	0.4	1.07 m		
Main upstream Head on HS1	0.4	0.2 m	0.21 m	The relative error between computed and measured water depth is 5%

Figure 5 shows the computed water level profile in the downstream channel of the main canal (6-7). The channel length is about 244 m. The computed water level is very close to the normal depth at the distance of 3.05 m. So, if the distance is greater than 3.05 m, the flow can be considered uniform at the depth of 0.49 m.

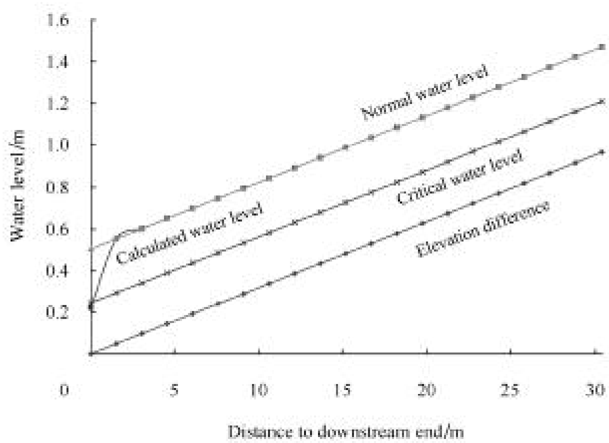

Figure 5 Computed water level profile of the main canal channel 6-7

Figure 6 shows the computed water level profile in the downstream channel of the lateral (5e-5g). The channel length is also about 15 m. The graphic indicates that the water level is going to but never reaches the normal depth. So, the flow in this channel is considered as pure gradually varied. The average water depth is about 0.23 m, which is 0.03 m away from the measured depth of 0.26 m (relative error is 12%).

Figure 7 shows the computed water level profile in the upstream channel of the lateral (5b-5e). The channel length is about 122 m. The computed water level is very close to the normal depth at the distance of 91 m. So, if the distance is greater than 91 m, the flow can be considered uniform at the depth of 0.37 m.

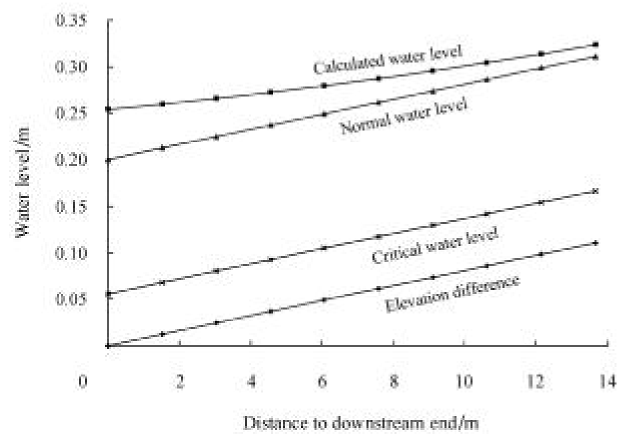

Figure 6 Computed water level profile in the downstream channel of the lateral 5e-5g.

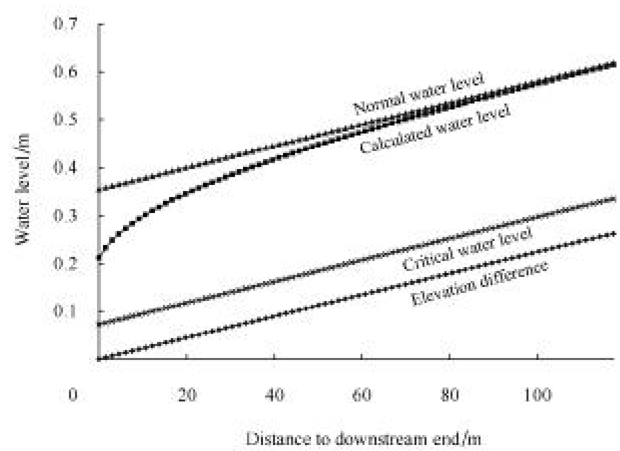

Figure 7 Computed water level profile in the upstream channel of the lateral 5b-5e

Figure 8 shows the computed water level profile in the intermediate channel of the main (4-5). The channel length is also about 244 m. The result indicates that the computed water level is going to but never arrives at the normal depth over the channel. So, the flow is considered as pure gradually varied. Using the depth curve, it can be derived that the 0.67 m water depth happened about 6.1 m upstream point 5, which matches the field measurement point.

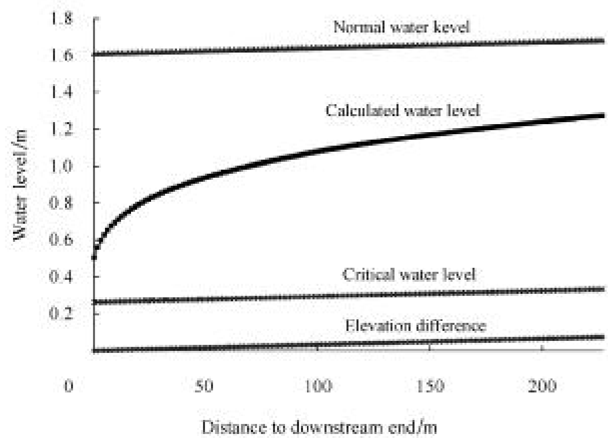

Figure 8 Computed water level profile in the intermediate channel of the main 4-5

Figure 9 shows the computed water profile in the upstream channel of the main (2-3). The channel length is about 1219 m. The water level is close to the normal depth at the distance of 244 m from the downstream end of the channel. So, if the distance is greater than 244 m, the flow can be considered uniform at the depth of 1.07 m.

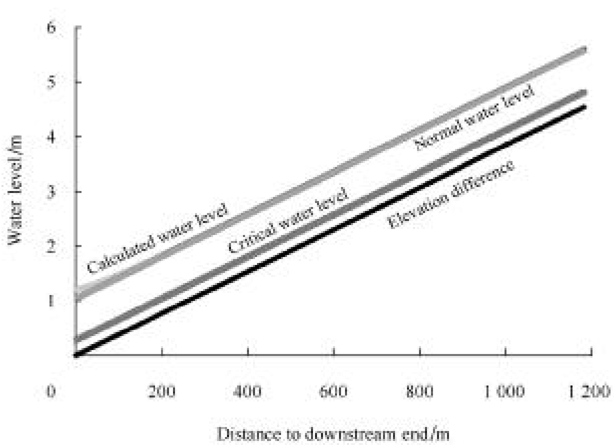

Figure 9 Computed water profile in the upstream channel of the main 2-3

Finally, the computation produced 0.2 m water head on the sharp-crested weir HS1, which is close to the measured depth of 0.21 m with the absolute error of 0.01 m (relative error is 5%).

7 Conclusions

This study has developed a tool for modeling the water flow profile in irrigation distribution networks. The modeling tool assumes SGVF flow in the branching canal networks. The tool starts the computation by initializing discharge and water depth at the end of the main canal and the laterals. It handles the branching networks in arbitrary layouts with first-level laterals. The method can be extended to the cases of arbitrary branching networks with second-level, third-level, and *n*-level laterals. The modeling tool was evaluated in water flow profiling for a single irrigation canal channel and an irrigation branching canal network. The calculations of the modeling tool had a 1% RMSE compared to the benchmark calculation of a single channel flow and 5% to 12% relative errors compared to check point measurement along a branching canal network. The implementation and results of the modeling tool indicated a strong capability in handling the modeling task in different conditions such that the modeling process with the tool becomes simple, fast, reliable and accurate with much less cost and least configurations compared to commercially available models and software packages. The outcome of this study will be able to play an important role in water quantification for planning, analysis and development for modernization of irrigation systems for irrigation districts in the Lower Rio Grande Valley of Texas and any other similar areas.

Acknowledgements

The authors thank Mr. Milton Henry, Director of Engineering & Technical Services, Jamaican National Irrigation Commission for his work in field survey and flow measurement. This work was partially funded with support from the Rio Grande Basin Initiative supported by USDA-Cooperative State Research, Education, and Extension Service (project no. 2005-45048-03208) and administered by the Texas Water Resources Institute.

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IJABE has been covered by Inspec

The International Journal of Agricultural & Biological Engineering (IJABE, http://www.ijabe.org) launched in 2008 has been accepted for coverage within the Inspec Database, after being successfully covered by Chemical Abstracts(CA), CAB Abstracts databases, and the CAB Full Text Repository.

The Inspec database is the world's largest and most comprehensive English-language bibliographic database, in physics, electronics and computing. Developed from **'Science Abstracts',** first published in January 1898, Inspec now scans over 4,000 journals (and other serial publications) worldwide, 2,000 conference proceedings and numerous books, reports, articles and dissertations, for inclusion in the database. From 1969 to the present day, the size of the database has grown to ten gigabytes of data and contains around **ten million** bibliographic abstracts and indexing to journal articles, conference proceedings, technical reports and other literature in the fields of science and technology.

Moreover, IJABE has been listed in the world's biggest open access journal platform, Open J-Gate (http://www.openj-gate.com) and Directory of Open Access Journals (http://www.doaj.org), which is very helpful to increase the visibility of IJABE.

(By Wang Yingkuan)

Appendix: Email notice from Team Leader of INSPEC Acquisitions

Dear Dr Yingkuan,

Many thanks for your email, and apologies for the delay in replying.

I am pleased to confirm the International Journal of Agricultural & Biological Engineering has been accepted for coverage within the Inspec Database as from the issues that you have sent.

Please can you send issues as and when they are published to myself at the address mentioned below.

Kind regards,

Jason Foulsham
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