Agricultural Activity Recognition with Smart-shirt and Crop Protocol

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***Abstract*—Accurate recognition of agricultural activity has a direct bearing on improving farm productivity in terms of achieving crop yield improvements, imparting precision training to farmers wherever needed, and measuring their efforts. Moreover, farm activities are not independent of each other. Cultivation of any crop is associated with a defined pattern of farmer activities called the crop protocol. With an indigenously developed garment for the farmer called smart-shirt, we propose a model for activity classification which has a mean activity prediction accuracy of over 88% for seven classes. The performance of numerous classifiers–SVM, Naive Byes, K-NN, LDA and QDA–is rigorously evaluated and compared for activity prediction. We also propose a model to use the a priori information associated with the crop protocol to recognize the major activity when presented with an unclear evidence of reported activities.**

Keywords–activity recognition, activity detection, activity prediction, crop protocol, package of practices, smart-shirt, machine learning, classification

I. Introduction

Agriculture is one of the key pillars of the Indian economy and similarly for many other developing nations. Specifically, India is home to several agro-climatic zones due to which there is a wide variation in the crop cultivation patterns across the country. Therefore constant endeavours have been made to improve the impact of agriculture through technology by introducing novel systems and services. Improving farm productivity through agricultural activity detection is one such endeavour in this direction. In agriculture, the timing of executing different activities plays an important role in determining quality of the produce. Further, in order to provide guidance and advice to the farmers, the knowledge of activities being performed is required. Accurate detection of agricultural activities is also useful to populate the farm diary which is used for several certification agencies.

Activity detection involving continuous monitoring of limb movements with sensor-enabled nodes has been done earlier for applications in health [1], fitness [2], manufacturing [3], and transport [4], [5]. In agriculture however, accurate detection of activities is a non-trivial exercise as it depends on many factors. For example, two or more activities with significantly overlapping features may make distinguishing between them difficult. The activity features for a farmer who has not yet trained may be substantially different from those for a trained farmer. Some activity for an untrained farmer may get misclassified into another activity.

In this paper, we use the contextual information of agriculture to accurately classify the manual agricultural activities like weeding, bedmaking, digging, sowing etc. We rely on the fact that the agricultural activities are not independent of each other as they follow a particular sequence of occurrence. Cultivation of any crop is associated with a particular pattern of farming activities which is also unique for a given geography and a cultivation technique. This pattern of agricultural activities is called *Crop Protocol* or *Package of Practices* (PoP). The knowledge of this a priori information of crop protocol when used in conjunction with the observed set of activities can be used to recognize the major activity.

We present the activity classification performance with an indigenously developed garment for the farmer, smart-shirt [6], which is able to achieve classification accuracy levels of over 88% for seven activity classes. Further, using these results as the prior knowledge of the crop protocol, we show how the performance of detecting the major activity from a set of reported activities for a given crop-stage increases from $\approx 54\%$ to $\approx 94\%$. The key contributions in this paper are: (a) a unique way to improvise the agriculture activities recognition performance by taking into consideration information about the crop protocol along with the standard method of using wearable motion sensors, (b) a Bayesian based approach to use the a priori information about the likelihood of an activity on a given day and a given plot of land for agriculture activities detection, and (c) considering new activity classes, features and classifiers with smart-shirt as the measurement system and the relevant performance comparison with previous work.

The background and motivation of the work is presented in Section II. In Section III, we present the activity recognition system based on smart-shirt samples collected from farmers. In Section IV, our work with seven activity classes and five classifiers is discussed where we compare and contrast the classification performance based on the features considered. In Section V, we present a probabilistic model on how the crop protocol is used to recognize the major activity from a set of reported activities (evidence sets) with our activity classification results as the prior knowledge. We propose a simulation model in Section VI which is used to generate a large number of evidence sets to rigorously evaluate the performance of the probabilistic model for detecting the major activity with and without the crop protocol.

II. Background and Motivation

There have been constant efforts to improve the impact of agriculture through the setting up of dedicated centres and services. There are two aspects to increasing farm productivity: maximising value of produce and increasing the crop-yield from farms. For example, in India, Krishi Vigyan Kendras (KVKs) are extension centres set up by the Government of India in every district of the country to cater to specific needs of each farmer. A KVK often has a weather station to record ambient parameters which are useful for forecasts. Similarly, there are dedicated portals such as AGMARKNeT [7] which give real-time crop price information to help farmers maximize the value of their produce.

There are two aspects to increasing crop-yield: (a) minimizing damage to crops by early detection of diseases or forecasting the onset of disease, and (b) engaging in the correct set of activities or precision farming on the farm at appropriate times to ensure that yield is maximized. Every crop has a defined set of phases from sowing to harvesting through which it becomes ready. It is important for the farm workers to know these phases and accordingly engage in the corresponding activities. In this paper, we discuss how activities performed by the farmers can be used to achieve farm productivity improvements.

Activity monitoring for humans using wearable sensors has been done with a combination of one or more sensors such as accelerometer, barometer, microphone, gyroscope, and magnetometer. A combination of accelerometer and barometer is used for fitness calibration of multiple activities such as cardio, walking, running, and flexing with Ubifit Garden [2]. Accelerometer and microphone have been used to classify workshop activities [3]. In the context of health, accelerometer mounted on ECG chest strap has been shown to model generalized active and passive postures of subject movement [1]. Similarly accelerometer based posture-recognition and fall-detection systems have also been proposed [8]. In order to provide for runtime adaptations in open-ended environments, an adaptive activity recognition framework (adARC) has been proposed [9]. Activity detection has been useful in transportation scenarios [4], [5]. Accelerometer based tracking has been used to determine the mode of transport (bus or underground) or if a vehicle has been used at all [4]. A combination of accelerometer and GPS is used to significantly improve accuracy of classification on the mode of transportation [5]. A recent survey [10] on activity detection work covering a variety of daily activities notes that a large number of studies use only the accelerometer while the remaining use a combination of accelerometer with another sensor such as gyroscope, microphone, pressure sensor, and magnetometer. It is further claimed that all sensors are not necessarily useful in all situations. For example, a gyroscope is unable to distinguish between the postures, sitting and standing. A combination of accelerometer and gyroscope works well to distinguish between walking upstairs and walking downstairs.

We note that limited work has been done on activity detection with respect to agriculture. Focused efforts in this direction include some of our previous work which included classification of some agricultural activities for a given crop based on a set of features obtained with an upper arm bound Android mobile tied to one hand [11], [12]. In the proposed work, we address the problem of agriculture activities detection based on accelerometer data obtained from both hands through an indigenously developed smart shirt. A comprehensive evaluation involving a large number of relevant features and numerous classifiers is performed with extensive comparison of performance results. Finally, we present our activity detection results in the context of the associated crop-protocol which can be useful in accurately recognizing the major activity given an observed set of activities.

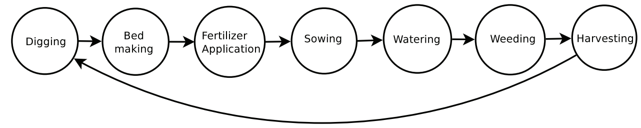

Fig. 1: Crop protocol stages

Crop Protocol and Farmer Activities

The decision by a farmer to perform any activity like sowing, pest-spray and others is taken on the basis of traditional cultivation practices, activities being done by the neighbouring farmers or based on the advisories by the farm experts. This activity usually proceeds in a sequence aligned with the protocol associated with the corresponding crop. The PoP for five major crops grown in India is given at [13]. Due to the various agro-climatic zones, the crop protocol may differ between zones. Crop protocol may also vary based on the cultivation practices being followed. For example, wheat is a crop sown in the winters and harvested in the summers. The crop is sown in November and harvested in May in the northern hilly zone of Kashmir whereas the harvesting happens much earlier, in February, in the peninsular zone of Tamil Nadu. There is however a distinct set of activity stages associated with the crop which is sowing, irrigation and harvesting.

Without loss of generality, the discussions in this paper are based on the Spinach crop, which is a common leafy vegetable consumed in the Indian sub-continent. The activities associated with the Spinach crop start with *digging* (harrowing) of the ground, preparing beds (*bed-making*), applying fertilizers termed *fertilizer application*, *sowing* seeds, *watering* the land, *weeding*, and finally *harvesting* the crop. Weeding can happen at different crop cultivation stages as and when weeds appear. The crop-protocol stages are given in Fig. 1. For the experimental analysis, the data has been collected using the acceleration sensors worn by some expert farmers at Yantra Park campus of TCS, located in Mumbai, Maharashtra region of India. We also propose an analytical model for recognizing the major activity for an observed set of activities given a history of recorded activities in the farm diary.

III. Farmer Activity Recognition

We have developed a smart-shirt (Fig. 2) for activity recognition which consists of two 3-axis accelerometers, one placed at each wrist, which are interfaced with an Android application that runs on a smartphone to receive the continuous stream of acceleration measurements for offline storage. The accelerometers are hereafter referred to as a_1 and a_2, and three axes for an accelerometer are denoted by x, y and z. The transfer of activity events to the phone happens over a wired interface, so there is no loss of data during collection. The data is processed offline at a central server and is used to train classifiers to recognize activities from accelerometer patterns. The recognition process involves collecting accelerometer data at the required sampling rate, preprocessing it for noise removal,

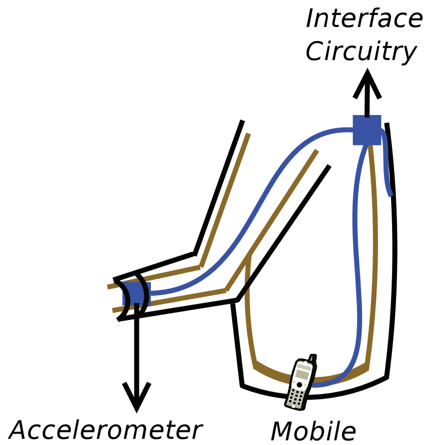

Fig. 2: Smart-shirt with accelerometers mounted at each wrist

extracting the required features for activity identification, and using the feature dataset to train the classifiers to recognize the activity for a given acceleration pattern.

A. Collecting Accelerometer Data

Having the appropriate sampling rate is crucial to avoid the loss of activity information. It has been noted that all human activities (more specifically hand-movements) are contained within a frequency of 20 Hz [10] implying that the ideal Nyquist sampling rate at twice the highest frequency component is 40 Hz. We use a sampling rate of 40 Hz which retains all useful information about the signal. We note that increasing the sampling rate has a bearing on the battery lifetime of the sensing system. Higher the rate, faster the rate at which battery is drained. Optimizing energy consumption is important in order to have the classification algorithms execute on the mobile in future.

B. Preprocessing for noise removal

Denoting a signal sequence for an axis by $s(.)$, the discretized signals $\{s(x), s(y), s(z)\}$ for $\{a_1,\ a_2\}$ are passed through a 5-point moving average (low-pass) filter to reduce the effects of noise. The signals are split into windows of subsequences for feature extraction where a window is denoted by $w_j, j \in I$. For human activity detection, a large body of work uses windows of the order of a few seconds, for example, 1 s windows with 52 samples [14] and 2.56 s windows (256 samples/window) at a rate of 100 Hz [15]. Some studies have evaluated various sizes such as 32 (1.5 s), 64 and 256 samples with 256 sample-window giving the best results [4] while others have used large window sizes of 8 s with two-thirds overlap [9]. For our case, the sequences are split into 64-sample subsequences with 50% overlapping which keeps the window size at 1.4 s [11]. Fig. 3 shows the windows over the sample sequence for a given axis. Also, a 64-sample sequence allows us to observe frequency domain features such as FFT which requires the sample size to be of the form $2^n, n \in I$ to avoid zero-padding.

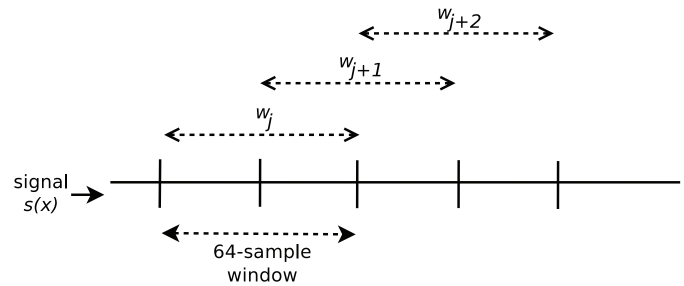

Fig. 3: Windows for an accelerometer signal for X-axis

C. Feature Extraction

The accelerometer signal generation conditions have to be understood well for effective feature-extraction. Feature extraction for activity recognition requires two aspects to be taken care of: position independence and orientation independence. Position independence refers to the ability to infer the activity irrespective of the position of the device used to detect it. For example, a *running* subject could have the device held in hand or placed in the waist-pocket, where each position would generate a distinct pattern. Two separate classes may be used to identify the *running* activity in these situations which are merged into a single class at a higher conceptual level [10]. Similarly, orientation independence refers to be able to classify activities irrespective of the orientation of the device used to capture the signals. This requires working with features that are less sensitive to device orientation such as the resultant acceleration rather than each of its components [15]. Although the accelerometers at the wrist in our smart-shirt have fixed orientation, we consider orientation independent features to keep our analysis generic and scalable to a broad range of similar devices, for example, mobile phones.

We collect the smart-shirt profiles with a large number of sample-points for the set of activities A={weeding, bedmaking, digging, walking, watering, sowing, fertilizer application}. We note that walking is one of the commonly observed activities along with the other activities as discussed in Section II. Accelerometers a_1 and a_2 have an operating range $\{-3g, 3g\}$ for each of their axes. We calibrate the smart shirt to identify the zero-g point for the axes from the raw measurements and use this to extract the (true) acceleration signals $\{s(x), s(y), s(z)\}$ for $\{a_1, a_2\}$. We then compute the resultant acceleration $r(a_1)$ and $r(a_2)$ for the accelerometers. Denoting signal sample i by $r_i(.)$ and $s_i(.)$, $r_i(a_1) = \sqrt{(s_i(x)^2 + s_i(y)^2 + s_i(z)^2)}$ and $r_i(a_2) = \sqrt{(s_i(x)^2 + s_i(y)^2 + s_i(z)^2)}$. The set of eight signals $\{s(x), s(y), s(z)\}_{\{a_1,a_2\}} \cup \{r(a_1), r(a_2)\}$ constitute the signal set we use for feature extraction. We call this signal set the *smart-shirt profile* for this activity and denote it by $K_c, c \in A$. For the rest of this section, we base our discussion on feature extraction from the smart-shirt profile for digging, $K_{digging}$. The profiles for digging and sowing are given in Fig. 4 and Fig. 5. Without loss of generality, the same principles hold for the remaining profiles as well.

For each member signal m in $K_{digging}$, we obtain a set of 210 windows $\{w_0, ..., w_{209}\}_m$. To ensure uncontaminated activity samples, we discard samples at the beginning and at the end of each signal while constructing the windows. Each win-

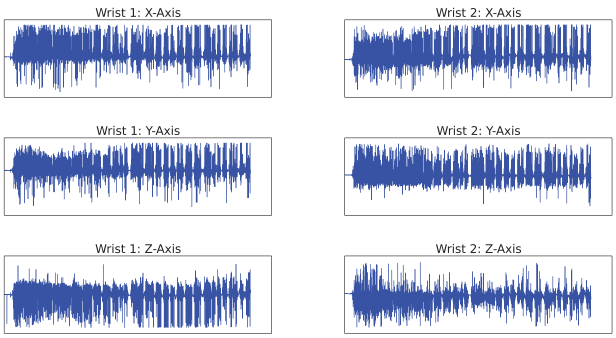

Fig. 4: Digging profile

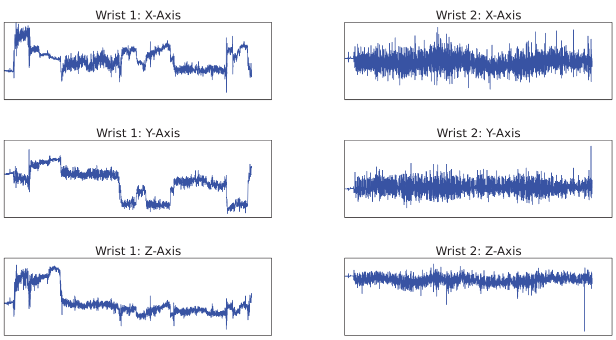

Fig. 5: Sowing profile

dow is used to compute a vector of features that is used to train classifiers for activity recognition. Retaining the significance of orientation independence, the first features we calculate are the mean (μ_j), standard deviation (σ_j), skewness and kurtosis of $\{w_j\}_m$ for $m \in \{r(a_1), r(a_2)\}, j \in \{0, ..., 209\}$. We note here that other time-domain features such as μ, σ, $\min$ (0%ile), and $\max$ (100%ile) for the signals $\{s(x), s(y), s(z)\}_{\{a_1, a_2\}}$ were separately considered as features for classification. However, they were found to be not as effective as resultant acceleration.

Correlation between axes is a measure of the degree of periodicity in a signal [15]. So, the next features we considered are the cross-correlation values for each axis of accelerometer, which is given as $\{corr_j(X, Y), corr_j(Y, Z), corr_j(X, Z)\}$ where $X = \{w_j\}_{s(x)}$, $Y = \{w_j\}_{s(y)}$, $Z = \{w_j\}_{s(z)}$ [11] We can see some periodic characteristics in the signal in Fig. 4 which would be different for different activity profiles. The last feature we consider is the frequency-domain entropy e_j of each window $\{w_j\}_m, m \in \{r(a_1), r(a_2)\}$ which is measure of information content in a signal. To calculate e_j, we first take the Fast-Fourier Transform (FFT) of the time-domain signal window w_j and compute the normalized histogram of the absolute values of the FFT spectral coefficients. Entropy $e_j = -\sum(p_i * log_2(p_i))$ for the histogram probability densities p_i in the window. Frequency-domain entropy is found to exhibit marginally better classification performance than time-domain entropy which is calculated from the histogram obtained from the time-domain signal without calculating FFT.

A total of 16 features are calculated and considered for training and testing the classifiers discussed in the next section for activity recognition. As there are 210 windows, a dataset with 210 entries where each entry is a feature vector, is considered. The entire set of features is given in Table I.

Features	Number
μ, σ, skewness and kurtosis of resultant acceleration for both the accelerometers	8
correlation between X, Y and Z axes of resultant acceleration for both the accelerometers	6
Frequency-domain entropy of resultant acceleration for both the accelerometers	2
Total features	16

TABLE I: List of features used for classification

D. Activity Recognition

Activity recognition involves training classifiers followed by testing them for activity recognition when presented with a new set of samples. The classification algorithms we consider include Support Vector Machines (SVM), Naive Bayes (NB), K-Nearest Neighbour (KNN), Linear Discriminant Analysis (LDA), and Quadratic Discriminant Analysis (QDA). Naive Bayes is one of the seminal classifiers which uses the Bayesian methods on the data to classify and recognize with the assumption that features are independent of each other. Naive Bayes makes a univariate class density assumption. Support Vector Machines classify data by transforming it into a higher dimensional feature space where the data becomes linearly separable. As the number of training samples are more than the number of features, we use the Radial Basis Function (RBF) as the kernel. We use the LibSVM (one-to-many) library to classify, train and test [16]. KNN works by preserving the entire history of events during training. At the time of testing, the K nearest points to the test samples are used to recognize the class. The K in this case is 5. LDA works with the assumption of a multivariate normal distribution for the class conditional densities, and tries to achieve a linear separation. QDA attempts to do a quadratic separation of the data instead of a linear separation with LDA.

IV. Performance Evaluation of Activity Recognition

An exhaustive dataset consisting of 210 datapoints where each datapoint is a 16-element feature-vector is generated for the set of activities considered. We divide the dataset into three classes D_1, D_2, D_3 with 70 datapoints each and perform a three-fold cross-validation to evaluate the performance of the proposed system. A three-fold cross-validation involves training with any two sets, testing against the third set, and repeating this for all combination of sets. Finally, the results are averaged to obtain the classification performance. Table II gives the classification results with SVM, NB, LDA, KNN and QDA. The mean recognition accuracy over all activities for each classifier is shown in Fig. 6. The mean accuracy over all classes is shown in Fig. 7. Mean recognition accuracy

Activity→ Classifier↓	Weeding (WD)	Bedmaking (B)	Digging (D)	Walking (WK)	Watering (WT)	Sowing (S)	Fert. Appl. (F)
SVM	81.55	91.79	81.64	89.86	99.52	78.74	83.57
NB	72.51	88.52	88.61	87.74	97.49	77.69	84.47
KNN	64.60	82.33	87.65	94.11	99.52	89.76	96.62
LDA	77.02	79.83	81.76	93.24	1.00	77.78	75.02
QDA	85.42	93.72	90.34	90.25	98.46	78.74	80.68

TABLE II: Classification performance results (%)

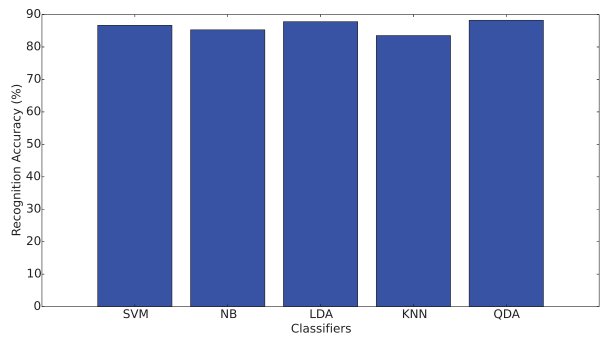

Fig. 6: Average recognition accuracy over all classifiers

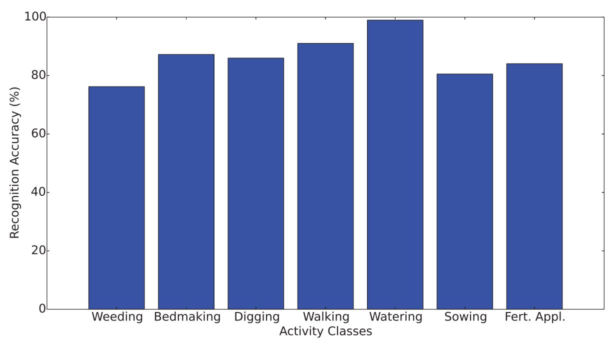

Fig. 7: Average recognition accuracy over all classes

lies between 83.5% and 88.5%. While the QDA gives the highest recognition accuracy at 88.23%, KNN gives the lowest accuracy at 83.52%. Both SVM (with accuracy 86.68%) and QDA give balanced results.

V. Using Crop Protocol to Improve Activity Recognition Accuracy

Let us assume a scenario that requires automated traceability of farm-activities, where the smart-shirt profiles are used to estimate the major activity during each stage of a given crop (say) Spinach. We further assume that the activity profiles used for our classification study above have been collected from a set of smart-shirt enabled farmers over the entire season. Using our activity-recognition results with QDA as the prior knowledge-base for a given activity in a given stage (refer Table IV), we propose a probabilistic inferencing method through which the actual activity in a stage can be obtained

Schedule (Days)	Crop Stage (Major Activity)
1–2	Digging
3–4	Bedmaking
5–6	Fert. Appl.
7–8	Sowing
9–10	Watering
11–15	Weeding

TABLE IV: Six stages of the Spinach crop protocol

Case	Classes
I	B = {Farmer is bedmaking} b = {Bedmaking event has been reported}
II	D = {Farmer is digging} d = {Digging event has been reported}

TABLE VI: Event definitions for establishing probabilities

from a set of reported activities for that stage. Table III shows the probability of major activities for different stages which have been derived from detection accuracies obtained with QDA as depicted in Table II. So $p(WD) = 0.8542$ corresponds to a recognition accuracy of 85.42% with QDA, and $p(WD^{'}) = 1 - p(WD)$.

Recognizing an Actual Activity

Let us assume we have activity profile information captured through smart-shirt for a given crop, say Spinach. We assume that the stage of the crop in the crop protocol is known to us. We propose a method that can be used to ascertain the actual activity during a stage when presented with an evidence of activities. These evidences could have been obtained by any means: visual inspection, manual farm records, devices other than smart-shirt.

We list down the probabilities of evidences for each activity for days 3 and 8 in Table V. Digging and Bedmaking are the major reported activities for day 3 with the evidence for both at 0.3. Similarly, for day 8, there is a conflict between three activities: Walking, Sowing and Fertilizer Application with all three at 0.2. Given such *noisy* data, the challenge is to recognize the actual activity for the days on which the evidences have been recorded.

For our discussion, we define two cases I and II given in Table VI where B and D refer to beliefs, and b and d refer to evidences reported for any given day. Let us consider

Activity→ Belief↓	WD	B	D	WK	WT	S	F
$p(Activity)$	0.8542	0.9372	0.9034	0.9025	0.9846	0.7874	0.8068
$p(Activity^{'})$	0.1458	0.0628	0.0966	0.0975	0.0154	0.2126	0.1932

TABLE III: Prior probabilities for crop stages obtained from QDA recognition results

Activity→ Observation↓	Weeding (wd)	Bedmaking (b)	Digging (d)	Walking (wk)	Watering (wt)	Sowing (s)	Fert. Appl. (f)
Day 3	0.1	0.3	0.3	0.1	0.1	0.05	0.05
Day 8	0.1	0.1	0.1	0.2	0.1	0.2	0.2

TABLE V: Evidence sets of activities on specific days of Spinach season

cases I and II for day 3 of the crop protocol which is listed as the bedmaking day for the Spinach crop (Table IV). From Table III, $p(B) = 0.9372$ and $p(B^{'}) = 0.0628$. For the sake of clarity and discussion, we assume $p(D) = 1 - p(B^{'})$ for day 3 where bedmaking is the major activity. These probabilities together constitute the a priori information available in the system that is used for making any recognitions for this day. More importantly, we need to ascertain the actual activity for day 3 given significant probabilities for bedmaking (0.3) and digging (0.3) in Table. V.

Case 1: With the belief B that the farmer is bedmaking, $p(b/B) = p(d/B) = 0.3$. We are interested in the posterior value $p(B/b)$ i.e. the belief that farmers are bedmaking in this phase given the observation b. For the evidence b, it follows from the theorem of total probability that

$$p(B/b) = p(b/B)p(B)/(p(b/B)p(B) + p(b/B^{'})p(B^{'}))$$

If x denotes a reported evidence of any activity, then $p(x/B^{'}) = 1$. Without loss of generality and with no prior information, we assume a uniform distribution for activities on $p(x/B^{'})$ s.t. $p(wd/B^{'})$ = $p(b/B^{'})$ = $p(d/B^{'})$ = $p(wk/B^{'})$ = $p(wt/B^{'})$ = $p(s/B^{'})$ = $p(f/B^{'}) = 0.143$. This gives $p(B/b) = 0.9691$. So, the belief that farmers are bedmaking given that 30% bedmaking events received on day 3 is 96.91%.

Case 2: Let us alter our belief that the farmer is digging (D) on day 3. The results conditioned on this belief $p(b/D) = p(d/D) = 0.3$. From our assumptions discussed earlier, $p(D) = 0.0628$, $p(D^{'}) = 0.9372$. Assuming a uniform distribution for evidence in the absence of prior information, we have $p(d/D^{'}) = 0.143$. The posterior belief for digging is given by $p(D/d) = p(d/D)p(D)/(p(d/D)p(D) + p(d/D^{'})p(D^{'})) = 0.2472$. The belief that farmers are digging given that 30% digging events are received on day 3 is 24.72%.

So, in the face of similar evidence for both bedmaking and digging, bedmaking should be considered as the major activity for day 3 since $p(B/b) > p(D/d)$. We note that the proposed method can be used to include prior information for multiple activities for all phases of the crop protocol for richer inferences. Without loss of generality, the same principle can be extended to other cases as well.

VI. Performance Evaluation of Crop Protocol based Actual Activity Recognition

With the principle outlined in Sec. V, we use simulation to rigorously evaluate how the crop protocol can introduce significant improvements in detecting the agricultural activity from a set of evidences of reported activities. The simulation model is used to generate a database of evidence sets in the format of Table V. In order to identify the actual activity in each evidence set, we compute the posterior probability of the beliefs from the prior beliefs and the evidence sets.

A. *Simulation Model for Construction of Evidence Set*

Let us assume that a set of activities are reported from the farm on a given day. Since farm operations are driven by the crop protocol, the reported activities for this day are naturally centred around the major activity. We assume a model based on the Normal distribution for generating the evidence sets where activities are assigned specific ranges (Fig. 8). While Major Activity refers to the expected activity in the current stage of the crop, Act2-Act7 refer to the remaining activities which also contribute to the evidence set.

To construct an evidence set E, we obtain N samples from the distribution. For each sample obtained within $\mu \pm \sigma$, we assign an activity based on the range {Maj. Act., Act2, ..., Act7} in which it occurs. The sample set is then normalized into into the set of probabilities that constitute E. So $E = \{p_x\}, \forall x \in A$ where A is the list of activities given in Table V. This model helps generate a large number of ambiguous evidence sets having activities besides the major activity with significantly high probabilities. Fig. 9 shows a histrogram of the evidence set samples with a majority of the samples concentrated within $\pm\sigma$. We note that using $\mu \pm 2\sigma$ and $\mu \pm 3\sigma$ with eight classes (two for major activity and six for other activities) is not very effective in generating ambiguous evidence sets.

In a sample evidence set E, the major activity is x where $p_x = \arg\max E$. Ambiguity occurs when there is at least one more activity $y, p_y \in E, y \neq x$ s.t. $p_y = p_x$. In an experimental scenario however, ambiguity can be ascertained through near equality i.e. when there is a margin of error e, $e = \|p_x - p_y\|$ where $e < T$ for a threshold T.

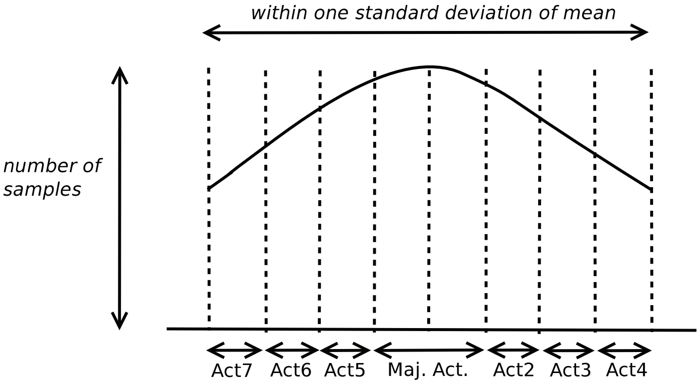

Fig. 8: Simulation model for generating an evidence set of activities

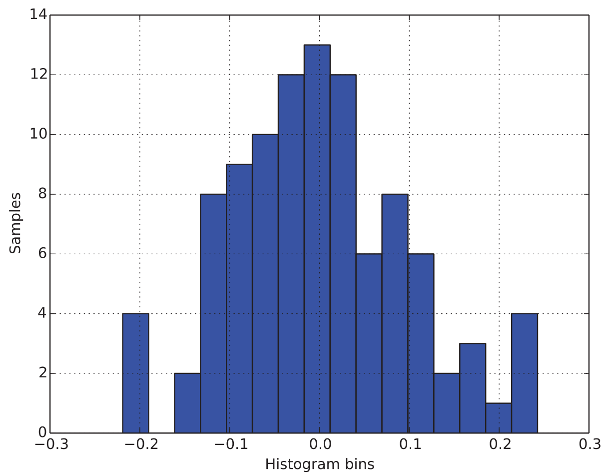

Fig. 9: Distribution of a set of samples used to construct an evidence set

B. Identifying Actual Activities from Ambiguous Evidence Sets

For all cases where the major activity is ambiguous ($e < T$), we first compute the posterior belief from the joint probabilities of the evidences in the evidence set and the corresponding set of prior beliefs. The difference between the beliefs is then compared against the error threshold T to establish the major activity.

From our discussion in Sec. V, the belief for each stage in Table IV is defined as probabilities of major activity and remaining activities as given in Table III. To obtain the posterior belief, the evidence set needs to be restructured to contain evidences for the major activity and the remaining activities. For example, the restructured evidence set E^{mod} for the day 3 evidence set $E = \{0.1, 0.3, 0.3, 0.1, 0.1, 0.05, 0.05\}$ with Bedmaking as the major activity is given as $E^{mod} = \{b, b'\} = \{0.3, 0.7\}$. This binary classification also addresses the situation where we have more than one non-major activity contributing to ambiguity in an evidence set. Then, we find the posterior beliefs, and the error e between posterior beliefs is used to establish the major activity.

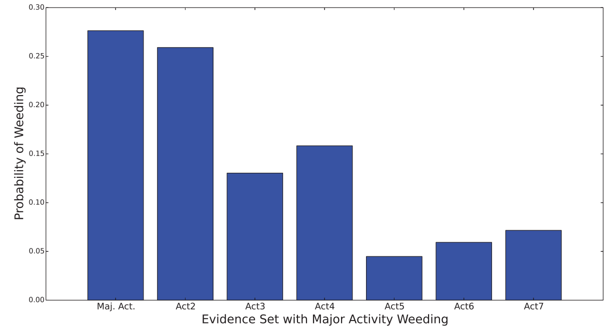

Fig. 10: Ambiguous evidence set with weeding as the major activity and one other activity within error threshold

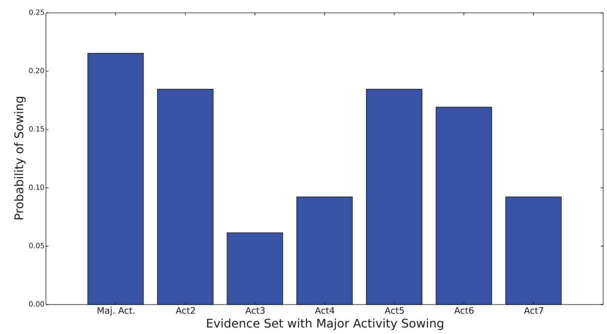

Fig. 11: Ambiguous evidence set with sowing as the major activity and more than one activity within error threshold

C. Simulation

The evidences that make up an evidence set are sampled from the simulation model (Sec. VI-A) with parameters $\mathcal{N}(\mu, \sigma^2) = \mathcal{N}(0, 0.1^2)$. We obtain a set of 100 samples ($N = 100$) to create an evidence set. Further, 100 evidence sets are generated for each stage of the crop protocol to take the total number of sets to 600.

D. Results and Discussion

From the 100 evidence sets obtained for each activity, Fig. 10 and Fig. 11 show the distribution of two evidence sets obtained for weeding (days 11–15) and sowing (days 7–8) respectively. With a threshold T of 0.1, both the sets are ambiguous although weeding and sowing have the highest probabilities. From Table III, we find that the prior belief for weeding and sowing are 0.8542 and 0.7874. With the first set, only one other activity is within the threshold while the second set has more than one such activities. From Table IV, we restructure these evidence sets based on the major activity as discussed in Sec. VI-B and then compute the posterior probabilities. For example, to calculate the posterior probability against these beliefs for the first set, we classify the evidence set elements into evidence for weeding and not weeding. From the principle outlined in Sec. V, we find for the first set that $P(W/w) - P(W^{'}/w^{'}) = 0.45$ and for the second set that $P(S/s) - P(S^{'}/s^{'}) = 0.25$, which are much greater than the

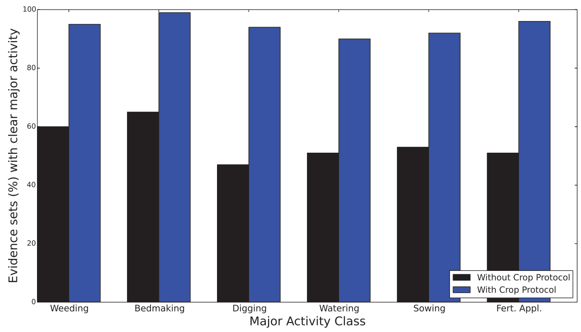

Fig. 12: Evidence sets (%) with clear major activity before and after considering crop protocol

threshold T. We note that if classification results with KNN were used instead of QDA to establish prior belief for the crop protocol then $P(W) = 0.6460$ and $P(S) = 0.8976$. Under these conditions, $P(W/w) - P(W'/w') < T$, so weeding would not be declared as the actual activity. Sowing however would still be considered as the actual activity.

With QDA results used for the prior belief, Fig. 12 shows the simulation results for the 600 evidence sets for each of the six stages of the Spinach crop. The bar graphs show the percentage of evidence sets with a clear major activity before and after considering the crop protocol. In the absence of crop protocol, the percentage of evidence sets with major activity ranges from 47% to 60%. When the crop protocol is considered, the performance improves substantially and ranges from 90% to 99%. The mean percentage of evidence sets without crop protocol is 54.5% while the mean increases to 94.3% with crop protocol.

VII. Conclusions

We have presented crop protocol based agricultural activity classification which achieves significantly improved performance over techniques proposed earlier. The improvements achieved with novel features and classifiers are highlighted. Further, we show with the help of Spinach crop how the crop protocol can be used to significantly improve the recognition of actual activity being performed on the farm given an unclear evidence of reported activities. We use simulation to rigorously evaluate the performance of activity recognition with and without crop protocol, and recognition performance is seen to improve significantly. We aim to take the principle forward to digitize various aspects of farm operations through agricultural activity recognition.

Acknowledgement

The authors would like to thank the gardening and farming staff and the administration team of TCS Yantra Park for their kind support in the data collection activities and in providing their sincere efforts in following our rigorous process to learn and perform the activities to provide us realistic data which has been extremely important towards the success of this experiment.

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