BARD Research Proposal Cover PagesTitle Page

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Title:
Development of A Robotic Inspection System for Early Identification and Locating of Biotic and Abiotic Stresses in Greenhouse Crops

Requested Duration: 3 years

Investigators

Investigator Position	Name	Affiliated Institution
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3)Collaborating	Tao, Yang	Maryland, U of

Suggested Evaluating Panel: Agricultural Innovation & Engineering Technologies

Requested Budget (in US $ **): $338,800**

Duration of Proposed Research: 3 Years

* Indicates an early career scientist (less than 5 years from first institutional appointment)

List of Abbreviations

2D Two Dimensions; 3D Three Dimensions; ARO Agricultural Research Organization, Volcani Center, Bet Dagan, Israel; ARL Agricultural Robotics Lab; ASAE American Society of Agricultural Engineers; CGMMV cucumber green mottle mosaic virus; CL Collaboration level; CV Coefficient of variation; CWA Continuous Wavelet Analysis; HO Human operator; HR Human Robot; HRI Human Robot Interaction; HS Hyperspectral; HSI Hyperspectral imaging; IAE Institute of Agricultural Engineering; I2S2 Integrated Image Sensing System; IR Infra Red; LADAR Laser Radar; LDA Linear discriminant analysis; LED Light emitting diode; MLR Multivariate Linear Regression; MSI Multi spectral imaging; MTMF Mixture Tuned Matched Filtering; NDVI Normalized Difference Vegetation Index; NIF Non-Imaging Flurometer; NIR Near Infra Red; PCA Principal component analysis; PLSR Partial Least Square Regression; PRISM Production, Robotics, and Integration Software for Manufacturing & Management; PU Purdue University; REIP Red Edge Vegetation Index; TSWV Tomato Spotted Wilt Virus; UMD University of Maryland; UV Ultraviolet; VIS Visual;

Contents of Proposal

Development of A Robotic Inspection System for Early Identification and Locating of Biotic and Abiotic Stresses in Greenhouse Crops

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Proposal Abstract

A major challenge in greenhouse crops is the inability to detect stresses and risks early enough to prevent uncontrolled spreading of stresses causing irreparable damage. Often, although the knowledge how to handle a stress is available, due to late detection it is too late to act correctly. Hence, farmers often react wastefully. Therefore, there is a compelling need to develop an effective, affordable robotic inspection system using close sensing and contact.

In greenhouse environments, the conditions are especially controlled to maximize the crops growth rate and production, which can expose plants to biotic and abiotic risks. Up to 40% of the world crop production is lost through diseases, insects and weeds, according to a 2013 estimate by the Food and Agriculture Organization of the United Nations. Due to scarce human resources, time limitations, and the high cost of current monitoring methods, mostly manual inspection procedures can lead to inaccurate use of nutrients and late detection of diseases. In addition, as farm sizes increase and the availability of labor decreases, more effective agricultural practices are necessary. A high frequency, high resolution and optimally planned crop monitoring apparatus, collaboratively supervised by a human operator to reduce cost, reinforced by agile robotics and spectral sensing technologies could lead to intelligent, efficient, safe, and more effective biotic and abiotic stress management.

The objective of this research is to develop and enable for the first time a human integrated intelligent sensory-robotic system for inspection and early detection of biotic and abiotic stresses and risks in greenhouse crops. This novel system will reduce human labor, reduce the amount of misused watering, pesticides and fertilizers, and detect and prevent in time the spreading of diseases.

The major specific advantages of the proposed systems which will be delivered by the end of this three-year project are:

1. An integrated human-robot collaborative algorithm and system for early stress detection and locating in greenhouse environment;

2. A sensing technology suited for robotic inspection to detect biotic and abiotic stresses in greenhouse crops as soon as they emerge;

3. Development of optimal trajectories and approach of sampling manipulator with 2D or partially 3D information; and

4. A prototype of a human-robot collaborative system for inspection of biotic and abiotic stresses in greenhouse crops, extendible in the future to early detection and locating of stresses beyond those studied in

the proposed project.

The project will lead to an innovative automatic system technology for solving practical problems in labor and production for farmers, and bring significant benefits and profound impacts to the US and Israeli agricultural industry.

2. Detailed Description of the Research Plan

2.1. Statement of the research problem and general background

A major challenge in greenhouse crops is the inability to detect stresses and risks early enough to prevent uncontrolled spreading causing irreparable damage. Often, we know how to handle the stress, but the detection is too late to act. In precision agriculture, remote sensing used widely to inspect and map variability in open fields is not suitable for protected crops: Certain data must be collected by contact with the plants, due to occlusion by a greenhouse roof, and requirement to inspect plants in variable spatial resolution and time frequencies. Thus, there is a compelling need to develop a ground inspection system using close sensing and contact.Experiments showed that contrary to common, mostly manual detection and identification approaches, a monitoring system comprising robotics and intelligent sensors can provide early and effective detection. Three drawbacks, however, have prevented so far the ability to construct and implement such systems: 1) no effective autonomous or Human-Robot Interaction (HRI) systems to perform inspections; 2) no adequate and precise sensor system integrating several sensors and sensor fusion algorithms suitable to perform in agricultural environments; and 3) no knowledge-based decision making system for the above two.

Our aim is to combine and integrate recently developed innovations in adjoining areas that will contribute to overcome the three drawbacks. An integrated testbed will be experimented for typical cases of biotic and abiotic stresses. These bio-stress test cases will enable us to examine and validate the abilities of the developed technology and system for inspection and early detection (in detection we mean identification and locating of stress) of a variety of biotic and abiotic stresses, extendible even beyond those stresses that will be tested.

Causes of stress and risks: Greenhouses conditions are especially controlled to maximize crops' growth rate and yield, which can expose plants to biotic and abiotic risks. Different biotic and abiotic stresses affect potential yield. Studies showed that 40% of food production is lost through diseases, insects and weeds worldwide (Oerke & Dehne,'04). During growing and harvesting stages, periodical, repetitive inspections must be conducted for stress detection. Yield-limiting factors should be detected as early as possible to apply appropriate counter measures. In the absence of affordable and effective monitoring, farmers' decision could be wrong and cause over/under implementation of pesticides, nutrients, and water. Nowadays, biotic and abiotic stress risks are handled wastefully: often by reapplying pesticides, adding nutrients (e.g., Nitrogen) and over-irrigating, even when symptoms thresholds are far from justifying it. Monitoring stresses during growing and harvesting in specialty crops is highly relevant for reaching plant production potential, maintain plant status, and prevent severe yield losses. Presently, monitoring for stress is manual in greenhouses. A person scouts on foot inside a plot, selecting locations for inspection, typically sampling a few plants or locations at each plot. Sampling locations are determined arbitrarily, usually in a fixed pattern. Even a trained inspector usually samples at low resolution, about 20 locations per hectare and can monitor up to 80 hectares per growing cycle. Each plot is monitored every 7-10 days; an inspector walks about 20km per day. Due to limited human resources, timeliness constraints, and high cost of such methods, the procedure can lead to inaccurate use of nutrients and late detection of diseases. As farm sizes increase and labor availability decreases, more efficient agricultural practices are necessary (Nagasaka et al.,'04).

When growing conditions subjected on a plant are not ideal, stress occur and symptoms typically appear on leaves and fruits, and can be detected by electromagnetic sensors. The source for stresses and non- ideal conditions could be biotic, i.e., diseases, or abiotic, i.e., insufficient or overdose of nutrients, water, and atmospheric conditions such as temperature, radiation, wind, etc.

Generally, monitoring crops' nutrition and water status is vital to control the plant development and obtain optimal yield. Yet, because now to evaluate nutrients level in soil involves sampling and delays in receiving lab results, most farmers do not monitor them. They conduct a visual follow-up to assess plant status. Insufficient monitoring results in overdose fertilization that impairs farmers' revenue and has negative environmental impact. The constant increase in fertilizers cost and decrease in produce profitability significantly justify the need to monitor nutrients' and stress levels. Similarly, an outbreak of diseases in commercial crops grown in structures usually emerges from few infected plants. The primary infection might occur due to invasion of insect vectors into a structure (e.g., aphids, whiteflies) as trips transmitting TSWV (Raccah & Fereres,'09) or for non-insect vector, i.e., contaminated soil or seed lots, e.g., CGMMV. These primary infected plants serve as an inoculum source for the secondary spread within a structure; therefore, early monitoring of the primary sources is one of the key factors in diseases and stress management.

The proposed project is driven by the current inability for early detection monitoring of stress symptoms, and aims to help farmers execute wiser methods to prevent the undesirable results. Recent projects have developed robotic based partial solutions to the problem (Gottschalk et al.,'08, Hu et al.,'14). Perceptive robots can be programmed to perform a variety of agricultural tasks, enhance quality of fresh produce, lower production costs, and reduce drudgery of manual labor (Bechar,'10). As described next, available and emerging non-destructive, more precise techniques for monitoring biotic and abiotic stresses offer methods that can be affordable by automation when performed with the aid of robots.

Emerging relevant techniques and technologies: A high frequency, high resolution and optimally planned crop monitoring apparatus, collaboratively supervised by a HO, enabled by agile robotics and spectral sensing technologies could lead to intelligent, efficient, safe, and more effective biotic and abiotic stress management. Simultaneous stress identification (Moshou et al.,'14a) applies data fusion of hyperspectral and fluorescence data to discriminate water stress from fungal infection in greenhouse plants. Similar efforts using remote sensing technologies indicate that MSI-based disease assessments were more precise and accurate than visual disease assessments for various foliar diseases including *Sclerotinia homercarpa* on bentgrass (Nutter et al.,'93), *Cercospora* leaf spot in sugar beet, and foliar diseases in alfalfa (Nutter et al.,'02).

***Agricultural robots*:** Research worldwide to develop agricultural robots has gained fruitful results. Technical feasibility for a variety of agricultural tasks was demonstrated, e.g., citrus (Hannan & Burks,'04), apples (Baeten et al.,'08), tomatoes (Kondo et al.,'96), cucumbers (Van Henten et al.,'09), transplanting (Chen et al.,'03); spraying (Stentz et al.,'02); harvesting (Sivaraman & Burks,'06); detection/ recognition (Van Henten et al.,'02), navigation (Khot et al.,'06). Despite advances, further research is needed, as explained on the three key drawbacks for the envisioned robotic inspection system.

All robotic technology, however, is domain specific; no universal robot can perform all tasks. In agriculture, unstructured environments demand robot motions and precise orientations beyond those in factories or in vehicle parking (Canning et al.,'04). Terrain, vegetation, landscape, visibility, atmospheric conditions are ill defined, uncertain, continuously vary and leading to unpredictable situations. Mission-specific robotic design and algorithms need to “program” robots to perform particular desired tasks. Furthermore, autonomous robotic solutions have yet to be successfully implemented due to lack of economic justification and production inefficiencies. Those are caused by limited autonomy and poor HRI leading to long cycle times and delays, low detection rates, and inability to perform in unstructured fields. Only few were implemented and are now in commercial use, such as autonomous combines and tractors (Schueller,'06). The drawbacks and inefficiencies call for solutions that incorporate HRI collaborative systems. Literature has little information on Ag. robotic monitoring systems; research has focused mainly on data collection and mapping, e.g., wireless positioning based on Kalman filter for sampling (Guo & Zhang,'05); field sampling with a GPS sensor (Demmel et al.,'02); integrated sensor to generate seed maps (Griepentrog et al.,'05). Robotic soil sampling was demonstrated by Liu et al., ('09) and disease detection algorithms for robotic monitoring (Schor et al.,'15).

Human-Robot Interaction (HRI): Agricultural applications of robotics require advanced technologies to deal with complex and highly variable environments and produce (Nof,'09) and not all horticultural applications can be fully automated in the near term. But partial autonomy can add value to the machine and its capabilities long before full autonomy is achieved. For many tasks, the Pareto principle applies, i.e., roughly 80% of a task is easier to robotize and automate (Stentz et al.,'02). Automating simpler parts of a task can typically reduce required manual work by 80%. An example is AGRIBOT, an HRI system to drive a robot through a field, from plant to plant and from row to row; to detect and locate fruits; to grasp and detach selected targets (Ceres et al.,'98). An integrated system engaged one HO to control multiple semi-autonomous operating robots in paddy fields (Nagasaka et al.,'04). Bechar et al., ('09) reported that, on average, HRI collaboration increased melon detection by 4% and 14% compared with manual detection and a fully autonomous system, respectively. This collaborative HRI resulted in high detection rates and could overcome limitations and costs of fully autonomous systems.

Sensing for stress identification and locating: Optical sensing (RGB and NIR cameras, HSI, thermal and chlorophyll fluorescence) was applied for early detection and monitoring water stress (Moshou et al.,'14b), nutrients levels (Corp et al.,'03, Portz et al.,'12), plant diseases (Oberti et al.,'14a). Fluorescence imaging is sensitive to early symptoms of foliar abnormality, and light reflection imaging can detect advanced symptoms (Lee et al.,'10). Alternative approaches to vegetables’ biotic and abiotic stresses include ultrasound (Mizrach,'08), but for standoff inspection of plants, optical imaging is more suitable. Thermal imaging and MSI have proven effective in plant biotic and abiotic stress detection, and 3D imager can capture plant canopy structure information: Thermal imaging variables to detect stress responses in grapevine under different irrigation conditions Grant et al. ('07); integrating thermal camera with LIDAR and stereoscopic vision to extract leaf features and annotation Nielsen et al. ('12); RGB and MSI cameras for disease detection on peppers (Schor et al.,'15). HSI, with tens or hundreds of spectral bands, was applied to stress/disease and weed detection (Mahlein et al.,'12). The keys to effective and efficient MSI and HSI applications: 1) Robust image analytics, e.g., feature extraction (Cheng et al.,'04, Panda et al.,'10); pattern classification (Sankaran & Ehsani,'12). 2) Real time processing (Alchanatis et al.,'05). Nutrients (nitrogen, magnesium, potassium, etc.) levels were detected applying SPAD device on plant leaves (Huang et al.,'15, Lin et al.,'10), indicating potential effectiveness of implementing optical sensors in monitoring for mapping plant nutrients status.

Further improvement of stress detection in greenhouses can be achieved via sensor fusion, especially with three dimensional (3D) optical imaging, which can reveal the structure of plant canopies and environment. 3D imaging technologies have been applied to agriculture, including stereo vision (Chane et al.,'13, Tarrío et al.,'06, Yuan et al.,'10), structured light (Chen et al.,'08) and time of flight (Chane et al.,'13, Dandois & Ellis,'13, Kang et al.,'12).

Combined complex tasks: To detect biotic and abiotic risks in greenhouses, robotic systems need to complete complex tasks. A cart roves between rows of crops. Manipulators mounted on the cart are maneuvering into a set of precise positions and orientations for sensing and detection. Sensors acquire measured data and fuse them to achieve high precision readings. To construct coherent coordination and reliable collaboration among subsystems, a knowledge-based planner software for the interrelated tasks needs to be designed. Early research on integrated planning for complex robotic tasks (Sammons et al.,'05) validated its advantages over stand-alone motion and grasp planning:(1) efficient utilization of limited physical and computational resources, (2) considering cross-domain interactions that impose hierarchical constraints on planning and control, and (3) complete global plans can be reused to satisfy real-time and timeliness requirements. For example, collaborative planning in assembly robots removes the barriers between robot task planning and product assembly planning so that manipulators can maintain maximum flexibility to accomplish more complex tasks (Rajan & Nof,'96a). Integrated task planning was advance by adaptive conflict resolution (Velasquez & Nof,'09) and combining geometry and task spaces. With the benefit of HRI collaboration, integrated planners will also generate dynamic plans for HOs in different collaboration spaces.

Proposed original innovations: The innovations in this proposal are two-fold.

1) New sensor system and fusion algorithms fitted for early detection of biotic and abiotic stresses by a HRI system. The innovation in the sensor fusion is its combination with a robotic system for early stress detection in greenhouse specialty crops. Also, the suggested mode of detection of abnormal situations is novel.

2) HRI algorithms and simulation to control and pre-evaluate the performance and operation of a sampling manipulator. To the best of our knowledge, there is no current system for stress detection that relies on HRI collaboration resulting in better, faster and more reliable stress inspection.

The objective: Enable for the first time inspection and early detection of biotic and abiotic stresses and risks in greenhouse crops by a human integrated intelligent sensory-robotic system. A secondary objective: Analyze, evaluate and observe limitations of the new system for the stresses examined, and its suitability for future expansion to early detection of other stresses.

The Investigators have conducted similar projects (some jointly) and are experienced in the technology and science required for this proposal. Using special imaging optics and cameras mounted on a robotic system, biotic and abiotic stresses and symptoms can be identified and located early, affordably, effectively and reliably.

2.2. Outline of research objectives

The overall goal is to develop a HRI collaborative platform for non-destructive inspection of biotic and abiotic stresses in greenhouse specialty crops, aiming to reach or exceed the crop yield and quality targets; reduce human labor; reduce the amount of misused watering, pesticides and fertilizers, detect and prevent the disease spreading. Moreover, the goal is to discover the principles for development of such affordable, cost-effective platform. The system will be partially autonomous, comprising imaging apparatus, a manipulator to execute precisely planned sampling, and algorithms to detect deviations in plant status, optimize sensors reach, approach and positioning of, integrate collaborative task requirements plans, and HRI collaboration (Fig. 1).

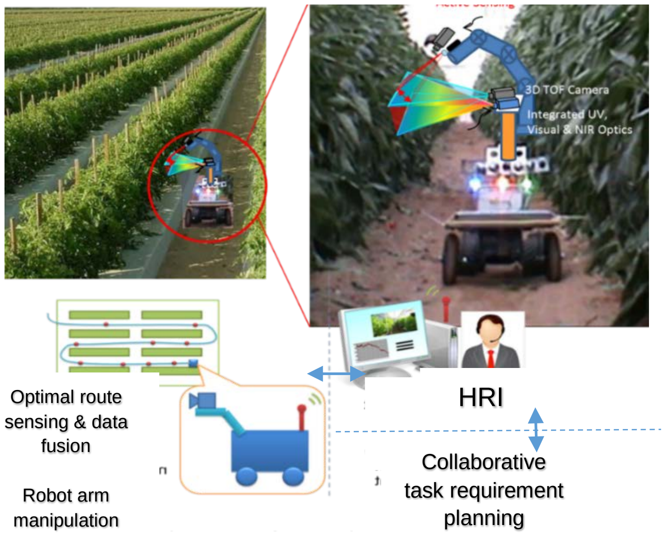

Fig. 1: Proposed human-collaborative autonomous robotic inspection system. (See Sec. 2.5.1. for details).

This research will overcome the three drawbacks stated above, including development, testing and adjustments of stress detection algorithms fitted for robotic inspection; collaborative planning for integrated tasks of sensing, manipulation, and HRI collaboration in greenhouse. Four specific, ambitious objectives must be met. Based on preliminary results we can accomplish much of them:

1. A <u>sensing system and algorithms</u> to monitor biotic and abiotic stresses in plants. This will be achieved by detecting early deviations in plant status and anomalies.
2. <u>HRI collaboration algorithms</u> to cope with the dynamic and unpredictable nature of the environment, including development of CL, adaptive, and learning algorithms.
3. <u>Trajectory and approach algorithms for a robotic arm,</u> required for precise visual contact.
4. <u>Integrated task Planner</u> to coherently coordinate the sensing system, manipulator, robot motion, and HRI collaboration. This will integrate the entire system to operate in greenhouse environments and overcome uncertainties.

<u>The outcome</u> will be a successful human-assisted autonomous robotic system that will be able to move along a plot, sample plants using precise visual contact, and report or flag early stresses caused by stated factors for prompt crop management. Benefits: New knowledge on HRI platform technology for greenhouse or row crop production; field labor reduction; and environment-friendly practices – significant advances even if we cannot achieve 100% of the goals. Based on our team's experience and preliminary investigation, this objective is reachable.

2.3. Hypotheses and their rationale

To the best of our knowledge, an autonomous or a HRI collaborative system for non-destructive monitoring of biotic and abiotic stresses caused by diseases or shortage/overdose of nutrients, fertilizers and water has not yet been developed anywhere in the world. Here we propose a novel sensor fusion approach for stress detection in a greenhouse setting by integrating MSI, thermal and 3D imaging technologies; deploying them through greenhouses with a HRI collaborative system.

Hypothesis 1: Multi-modality imaging sensor fusion of thermal, 3D and MSI (color and NIR, optional UV fluoresce) will improve: 1) with minimal human intervention, the detection in plants of common biotic stresses such as Powdery Mildew, CGMMV, TSWV; 2) nutrients level detection, e.g., nitrogen, magnesium or potassium; and, 3) water stress, appearing in greenhouse crops like cucumber, pepper, tomato. The rationale: Thermal imaging and MSI have proven effective in plant stress and abnormality detection; plant canopy structure details can be captured by 3D imager. By multi-imaging modalities synergy it becomes a powerful tool to identify, locate, map and trace plant stress dynamics precisely, automatically, with unprecedented spatial and temporal resolutions.

Hypothesis 2: HRI collaborative systems will outperform in agricultural environments both fully autonomous and manual systems, when robots with sensors, fast computing, and moderate machine intelligence replace just tedious labor intensive walk and repeated inspection motions, while humans supplement intelligence and knowledge that a robot may request. The HRI system identification and locating performance will be (1) more effective and less costly than a fully robotic system (e.g., high hit rates, low false alarm rates); (2) its total performance including detection and operation time will be faster than a human worker, or a fully robotic system. The rationale: Humans have superior perception, thinking and action capabilities; can easily adapt to changing environmental conditions and unforeseen events. By taking advantage of human perceptual faculties and the robotic systems' accuracy and consistency, the combined HRI system can be simplified, overcome drawbacks and barriers, resulting in improved performance, presenting a viable response to many pressing needs of automation (Burke et al.,'04). Integrating a HO in a robotic system can improve performance, hence increasing farmers' acceptance, by reducing the complexity of a fully robotic system (Parasuraman et al.,'00). The rationale is also based on reported results (Bechar et al.,'14a, Bechar et al.,'09, Oren et al.,'12) showing that HRI is superior to fully autonomous and to manual systems in such environments.

Hypothesis 3: Integrated task planning for the entire system (sensors, human, and robot) will yield better performance in handling complex early identification and locating tasks on a timely basis, with several layers of subtasks. The rationale: algorithmic collaboration requirement planning, e.g., of tasks, motion and orientation trajectories, generates coherent control plans for the collaborative execution by subsystems (Nof & Chen,'03, Rajan & Nof,'96b, Rajan & Nof,'96a) so they will achieve: (1) simplified input/output interface with HO supervisory control (Bechar et al.,'14b); (2) efficient utilization of onboard computing resources with reusable solutions and learning functions (Zhong et al.,'15), e.g., of vision-led approach motions; (3) integrated planning considering constraints from different subsystems and HO, e.g., overcoming unexpected obstacles to sensing approach (Kaelbling & Lozano-Pérez,'11); (4) collaborative error detection and prevention, or resolution, for fault tolerance, e.g., for adjusting integrated motion and sensing plans (Jeong & Nof,'09, Oren et al.,'12). Integrating HO into a robotic system will not impair 'timely detection' since most time spent in current manual inspection is on moving between locations, not due to actual manual inspection time.

All algorithms and technologies developed, e.g., the imaging technology; sensor fusion approach; sampling manipulator trajectory algorithm; HRI for planning integrated tasks, will be designed, tested and validated especially for unstructured greenhouse environment.

2.4. Preliminary Results

An adaptive algorithm for navigation of a robotic sprayer in pepper greenhouses was developed and tested by the PI on both an experimental robot (also developed by the PI, Fig. 2a) and a commercial sprayer (Fig. 3). The adaptive algorithm is based on a modified decision tree, yielding on average 93% success (fig. 2b & c) at different illumination and sun direction conditions (Dar et al.,'11).

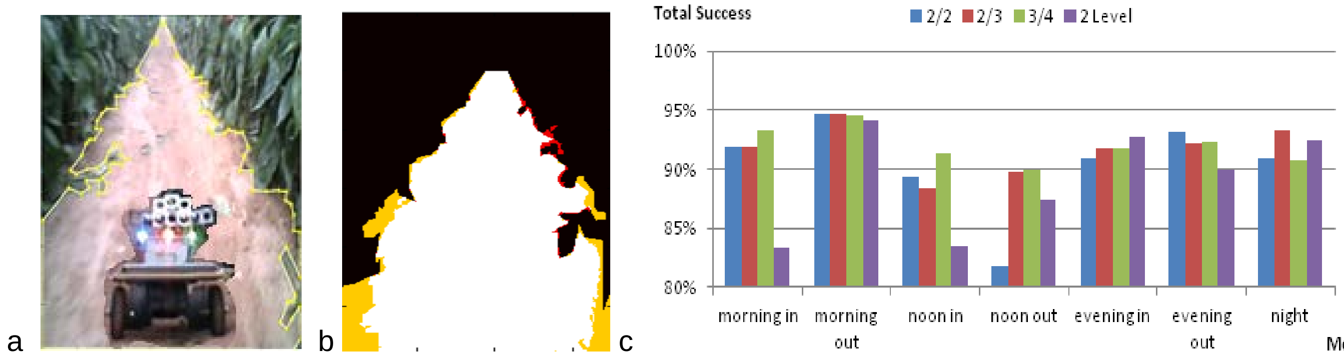

Fig. 2: Navigation experiments given:a) experimental robot in commercial greenhouse; b) adaptive algorithm performs on (a); c) Preliminary results: Adaptive algorithm at different conditions/ scenarios, yielding on average 93% success.

In greenhouse experiments, the experimental and commercial, platforms navigate successfully without contact with plants or obstacles. A deciduous Tree selective pruning robot was developed at ARO with algorithms to optimize reaching orientation and navigation with (Fig. 4 L) and without (Fig. 4 R) plant 3D geometry, and visual servoing with HRI or computer vision. The HRI collaborative system was developed with manipulator, color camera, laser distance sensor, HMI, and cutting tool. In experiments, it yielded average cycle time of 9.2s with errors less than 22mm, when the HO and the robot executed simultaneously (Bechar et al.,'14a). Early pepper plants disease detection algorithms for robots were developed (Fig. 5) (Schor et al.,'15) based on principle component analysis and variation of disease pattern, yielding 85-95% accuracy.

Recent integrated robot task planning (Table 1) in four areas can contribute to the new HRI system. Purdue PRISM lab directed by Dr. Nof pioneered collaborative control theory, algorithms, protocols, and patents, deployed in hybrid human-automation applications. Besides manufacturing and inspection, they include supervisory and sensory early detection of hazardous patterns in monitored facilities, operating under uncertain conditions. These solutions are applicable to the proposed study, and will be adapted with the sensors described below to agricultural constraints.

Although several recent research techniques for identifying and locating stresses (Table 2) can be fitted to robotic systems, none of them was developed specifically for it. Their detection earliness is medium-advanced; detection precision - medium, both inadequate for a robotic monitoring, identification and locating system.

Fig. 3: modified unmanned commercial sprayer in a lab greenhouse.

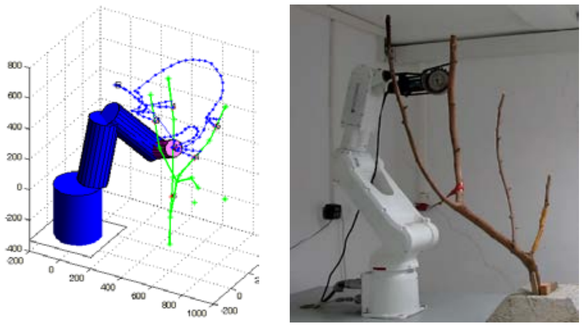

Fig. 4: Optimal trajectory in tree pruning (L) navigation problem in 6 dimensional configuration space; (R) visual servoing with HRI/ computer vision.

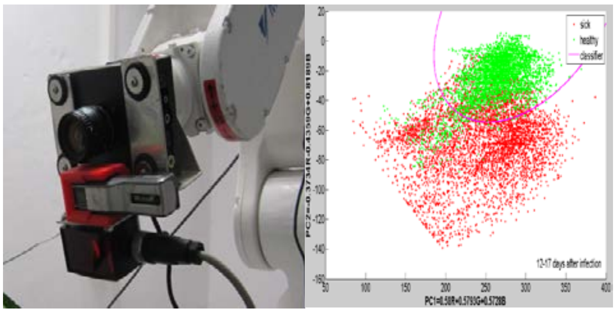

Fig. 5: Preliminary disease detection apparatus: End effector and sensor system (L); Principal component analysis of healthy (green) and diseased (red) plants (R).

Table 1. Recent research by PIs and others relevant to the proposed integrated robot task planning.

Area	**Contributions**	**Example references**
Hierarchical task network (HTN)	Improve search efficiency in large task space; hierarchical solutions for subsystems.	(Cardoso et al.,'11, Wolfe et al.,'10)
Integrated task and motion planning	Integrated planning for task space and geometry space.	(Erdem et al.,'11, Kaelbling & Lozano-Pérez,'11)
Error prevention/recovery and conflict resolution	Adaptive collaboration plans include error recovery strategy; learning capability to recover from identified errors, conflicts	(Jeong & Nof,'09, Nof & Chen,'03, Tkach et al.,'11b, Velasquez & Nof,'09).
Human-robot collaboration	Mechanisms for switching between collaboration levels (CL); intuitive human-robot interface with fault-tolerant control.	(Bechar et al.,'09, Bechar et al.,'14b, Tkach et al.,'11a, Zhong et al.,'13)

Table 2. Recent research relevant to detection, identification and locating of powdery mildew (grey background), nitrogen (white background) and water (black background).

System type	**Where**	**Field use**	**Software, Algorithm**	**Detection Earliness**	**Precision**	**Fitable for robot**	**Equip. cost, K$**
Multi-spectral Reflectance Spectrophoometer	Lab	Maybe	Filtering, Statistical analysis, LDA, PCA, PLS,	Medium to advanced	Medium to high	Maybe	2-5
Laser UV Induced Fluore. *(Buerling et al.,'12)*	Lab	Maybe	fluorescence amplitude ratios, mean lifetimes	Early: 2nd day	High	Maybe	5-20
Laser UV Induced Fluore. Imaging Flurometer) with CCD Camera	Lab	yes	SAS, image correction, fluorescence ratios and edge detection.	Early	Medium-High	yes	10-30
HSI,MSI, *(Franke & Menz,'07)*	Field	yes	Spatio-temporal analysis,MTMF,NDVI	Medium to advanced	Medium	Yes	6-16
HIS (UV/VNIR *(Zhang et al.,'12)* Spectroradiometer)	Lab	yes	CWA, MLR, PLSR	Medium to advanced	Medium	Yes	3-10
HSI, spectrometer ,*(Oberti et al.,'14b)*	Green house, Field	yes	Discriminant functions: PPV,NPV, RIR Specificity,REIP,.	Medium to advanced	High	Yes	6-16
Spect. Reflectance with Halogen Light. (Cohen et al.,'10)	Field	yes	Optical index, TCARI), PLSR.	*	Medium / high.	Maybe	1-3
SPAD (Nyi et al.,'12)	Lab	yes	Regression models.	*	High	Yes	2-5
HS Reflectance SpectroRadiometer (Jain et al.,'07)	Field	yes	PCA, ANOVA. regression, indices at 750 & 710 nm.	*	Low/ medium	Maybe	2-16
SpectralReflectance with Halogen Light Fiber-Optics Probe (Rotbart et al.,'13)	Field	yes	PLSR, LTCAL software.	*	Medium / high	Yes	4-10

Spectral Reflectance RapidSCAN CS-45 Portable Sensor	Field	yes	NDVI / NDRE, statistics. Crop/soil reflectance at 670, 730 & 780 nm.	*	Unknown	Maybe	1-5
Thermal imaging system (Alchanatis et al.,'10)	Field	yes	Image processing	Early/ medium		Maybe	30

* Vegetative and tuber-bulking.

Work at the University of Maryland Bioengineering focused on high speed HSI, active 3D imaging (Fig. 6), and vision sensor fusion (Fig. 7). In these studies, tasks including video acquisition, image processing, pattern classification and data visualization were conducted in real time, and the related technology and know-how can be applied to this proposed study.

Fig. 6. 3D laser scanning of plant canopy structure. It provides the XYZ(depth) information in real-time. (Brighter pixels are closer to the camera in depth Z)

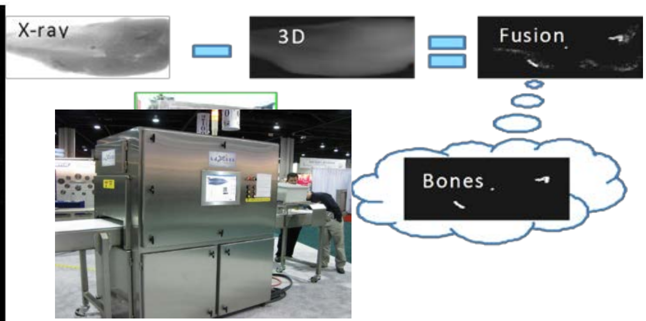

Fig. 7. Sensor fusion of x-ray imaging and laser 3D imaging for bone fragment detection in processed meat, inspecting tons of products daily. Sensors of different principles provided extraordinary sensitivity and accuracy.

2.5. Research Plan

2.5.1 Strategies, procedures and methodologies used in addressing the research questions

The proposed 3-year research is interdisciplinary, with methods and techniques from agricultural, industrial and mechanical engineering. It focuses on detecting symptoms of biotic and abiotic stresses on foliar: powdery mildew (biotic), water (abiotic) and nitrogen (abiotic) in peppers and tomatoes grown in greenhouses. Powdery mildew is one of the most common, serious threats with severe consequences to greenhouse crops production. Heavy epidemics can cause significant yield loss, i.e., 2-4 kg/m2 (Cerkauskas & Buonassisi,'03).

Four tasks are planned to develop and integrate the research, comprising: a sensing system, sampling manipulator, HRI interfaces, integrated task planning module, and additional subsystems. The sensing system will integrate multi-modality imaging (MSI, thermal, and 3D cameras; compass and LADAR system) for navigation and anomalies detection. The manipulator will deliver sensors precisely to sampling points/ targets, especially when visual contact with particular plant area is required. For nitrogen detection, a SPAD Chlorophyll sensor will be used mounted on the manipulator to measure chlorophyll in leaves. A trajectory/approach algorithm will be developed to bring the SPAD to physical contact with foliage, following preliminary work by Bechar et al. ('14a).

We will focus on identification and locating of early to medium deviations in crops, possibly indicating presence of anomalies and stresses in plants. Geometrical dimensions of the platform will be designed for traversing rows and inspecting internal layers of the canopy if needed.

Integrated task Planner onboard the robotic system will generate control signals for collaboration of sensing, manipulator, and motion subsystems. It will also communicate with HRI collaboration interface, requesting human input at different CL according to specific tasks and current conditions.

Previous technologies and algorithms developed by the researchers for navigation, detection, HRI etc. will be modified and adjusted for this project, as explained next.

2.5.1.1 Development of the multi-sensor imaging system

Sensor system development will be in laboratory conditions, where calibration and basic functionality are based on simulated crop conditions and using feedback through visualization of symptoms related to crop health status. Biotic and abiotic stresses under investigation, all have potential to be effectively detected by different vision systems/ cameras. MSI and canopy structural 3D imaging will be used for biotic stresses detection, to determine spread of stress factors in entire plants, for early detection of changes in plant vitality, and to discriminate between stress factors with similar spectral impact. Fluorescence imaging and fluorescence kinetics (by a handheld fluorimeter mounted on a manipulator) will be used for pre-visual detection of stresses. Stresses could influence leaf/plant temperature, therefore we will use an inexpensive good quality thermal camera to detect very early deviations in the plant temperature, in addition to a vision system for detecting initial visual symptoms. To compensate for leaf orientation (Grant et al.,'07), thermal will be used in combination with Red/NIR 2-CCD camera which can extract leaf features and annotations, or with an inexpensive thermal imager. An initial design of the proposed Integrated Image Sensing System (I^2S^2) consists (Fig. 8) of a thermal, MSI, and 3D imaging cameras. Related components (control, lights, cables, processing and user/robot interface) are omitted from the figure for clarity.

A multiplexed multi-purpose lighting system will be used on this robotic system. Artificial lights (LED matrix) will be switched on to supplement natural light if illumination is low. Camera's AGC can be turned on as needed to enable dynamic range of imaging. Active red laser in 635nm or 650nm for 3D imaging (Figs. 6, 7) works well in natural ambient light by using a narrow band optical filter peaked at the laser wavelength in front of the camera lens. Optionally, in addition to the fluorimeter mentioned above, LEDs peaked at 365nm UV-A can be switched on to fluorescent imaging inspection of a disease, as necessary. All those multi-purpose light components can be implemented at low cost.

For nutrient level measurement, in addition to the above, a SPAD sensor will be, mounted on the manipulator to measure chlorophyll levels in leaves that come in contact with it. Using a 3D image of foliage, a trajectory algorithm will be developed to ensure physical contact between SPAD and leaf. These SPAD measurement results will be compared to those obtained with it manually, by an HO.

All imaging subsystems (thermal, MSI, 3D, etc.) will be tested and commissioned so that feasible solutions, including hardware setup and data acquisition software are ready for field tests. The Bio-imaging & Machine Vision Lab has extensive experience in automated imaging detections.

2.5.1.2 Data acquisition and sensor fusion

Stress factors affecting biochemical processes in plants can alter spectral response, therefore, multispectral signature combinations from different spectral bands (VIS and NIR) can lead to appropriate interpretation of a plant's health condition. Thermal image in mid infrared range will be taken and treated in conjunction with canopy structural 3D and 2D features. These features might also aid sampling spot locating for the other sensors. Data from different sensing systems where combined experiments are performed (thermal, MSI, 3D) will be integrated with adaptive data fusion architectures: image fusion, feature based on learning algorithms or Bayesian/ probabilistic fusion, depending on situation/content/ requirements. Sensor fusion diagrams (Fig. 8) will integrate spatial data features from a 3D camera and geometrical features using morphological analysis from MSI and thermal cameras and color-based features to detect anomalies from MSI and thermal cameras.

Specific algorithms will be developed based on available literature (above) and by UMD Machine Vision Labs and ARO. Generally, algorithms such as Support Vector Machine (SVM) and supervised learning, Artificial Neural Networks (ANN), PCA, LDA and other useful statistical-based pattern recognition methods can be applied for specific problems (CV, (Schor et al.,'15)), using training of samples. Data and results will be shared via Internet among the team. Dr. Tao's Machine Vision Lab at UMD has comprehensive experience in algorithms development for automated pattern recognition and defect/disease detections.

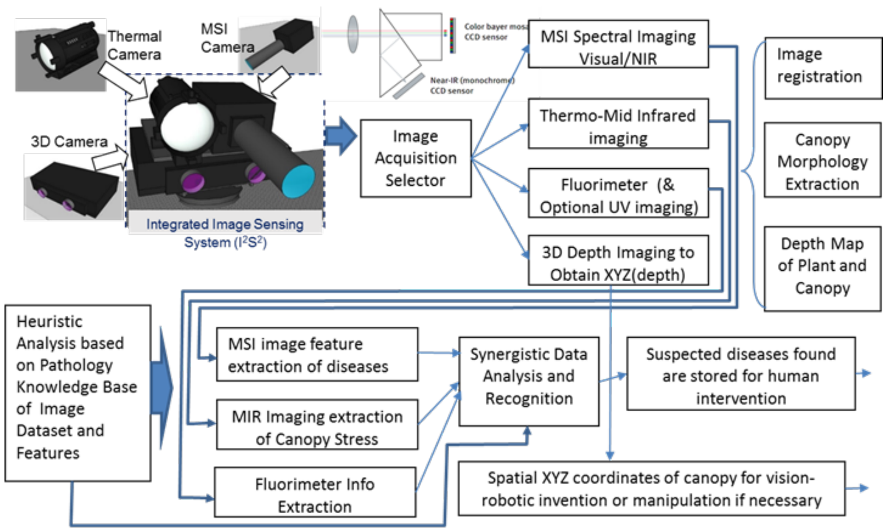

Fig. 8. The proposed Integrated Image Sensing System (I2S2) for plant stress detection (upper left) and logic flow of multi-sensor imaging system for the disease detection.

Data will be acquired to contrast threshold detection levels, reproducibility and reliability (false positive and/or false negative rate) of visual and image-based stress patterns at increasing severity levels, based on increasing symptom levels and severity over time. Datasets will be collected at the University of Maryland greenhouse on campus, to which Dr. Tao has access (on another collaborative project with plant science). Dr. Tao's bioengineering department has also its biotech institute greenhouse facility at Shady Grove campus. UMD has a large experimental farm that can also be requested to use. On the collaborative site, PI Dr. Bechar of ARO has collaborative access to greenhouse facilities at ARO. Datasets including images can be shared and transferred via web for image processing and analysis. Live remote computer access in data collection can be done using TeamViewer™, which allows real-time instant access to each other's computer/robotic system via high-speed internet as if operating locally. Dr. Tao's lab has used TeamViewer for remote control of their machines in the field (as in Fig.7) across the US for system operation, trouble shooting, and diagnostics. During data acquisition, different signal combinations will be gathered by a multisensory detection system capable of stress detection. Data quality from single sensors will be contrasted for cost/benefit of low-cost sensors while retaining higher accuracy through fusion. Decision making for biotic and abiotic stress detection will be based on extracting appropriate multimodal signatures from sensor data, associating them through feature- and statistical-based pattern recognition algorithms stated above and practiced successfully in various imaging detections at Dr. Tao's lab at UMD, Dr. Bechar lab at ARO, and remarkable work by other labs in literature cited above. Machine learning ability will be added in the system to associate obtained signatures to observed conditions of crops, and achieve automated stress determination. Attention will be given to data fusion for increased accuracy of stress identification and anomaly detection algorithms for real-time detection and locating of threats. More extensive description of algorithms can be given, but comprehensive equations are omitted due to page limit of the proposal.

2.5.1.3 Prototype sensing platform

The sensors and data fusion (sections 3.5.1.1-2) will be integrated in a mobile prototype platform for plant stress detection. Lab and field experiments will be conducted to test the prototype sensing platform performance. Greenhouse evaluation, and optimization of the prototype sensing platform will occur after obtaining feedback from the experiments. The equipment and imaging devices will be shared among labs of U.S. and Israel team members of this proposal. Imaging and data results can be shared and communicated via Internet as stated above.

2.5.1.4 Integrated Human-Robot Interaction (HRI) collaborative system

To cope with dynamic, unpredictable nature of the environment and keep system performance and reliability at high level, HRI collaboration algorithms will be developed, including CL, adaptive, and learning algorithms based on technology developed by both Dr. Bechar and Dr. Nof in previous research (Section 2.4). Previously validated TestLAN algorithms and protocols for collaborative monitoring and testing applications (Williams et al.,'03) will be adapted for optimal dynamic task/resource allocation, and detection task scheduling (Zhong et al.,'15). The system will be able to transfer images and data to non-expert HO, or an expert in case of difficulties to complete certain detection tasks, such as temporary inability to interpret stress information, or marking sample targets to the manipulator. A HO will be able to control the system at different levels of collaboration (CL), from defining robot operating rules, to supervisory control. In most cases, human input is given offline and saved apriori in a robot knowledge base. Modes of episodic learning with Big Data approach (active and on-demand learning with the robot requesting help from supervisor) and adaptive algorithms will be developed and implemented for dealing with abnormal situations in biotic and abiotic stress identification and locating, in cooperation with sensing tasks. A collaboration system will be developed and integrated with the platform, the manipulator, and the sensing system, as in Fig. 9.

The CL is determined by the Planner algorithm of the robotic system as a multi-objective decision problem. An objective function/model will be designed to determine the expected value of the mission performance and evaluate the influence of CL. This function will combine multiple performance measures, modeled with parameters in five categories: human, robot, network, environment, and mission. It will indicate what the best CL is and what should be the optimal collaboration parameters in the current conditions. The models will apply the objective function to understand the effects of different HRI CL on tasks performance. Sensitivity analysis will be developed and tested over selected parameters to determine their influence and find the best CL, type of interaction, resulting objective function and performance measures. The results of this task will guide the development and characterize the testbed and the collaborative system.

The Planner near the HRI interface (Fig. 9) will also coordinate with other subsystems to plan tasks and sub-tasks for all engaged subsystems: (1) Route plan to guide roving motions of the robot cart to sample stresses in a greenhouse; (2) Contact plan to issue requirements of how the manipulator mounted on the robot cart should approach a good sensing position; (3) Sensing plan, matching pathology patterns and sensors, to issue requirements for what data to acquire by which sensor, when to fuse data, and whether the collected data are sufficient for conclusive detection.

In this architecture, HOs can supervise the robotic system online, possibly remotely, but human intervention to robots is not needed continuously, same as a supervisor does not have to tell workers all the time what to do on a job. Most commands of robot activities are issued by the integrated Planner. According to the system structure, the robot cart is the base for the manipulator which is holding the sensing subsystem. Integration of plans becomes essential since individual plans cannot operate subsystems alone to effectively achieve the system's goal.

The developed system and HRI interfaces will be designed for the following HO requirements: The HO can be an agricultural inspector, a farmer or a worker with inspection abilities in order to make decisions, direct the robotic system to suspected locations of selected parts on the plant based on images and information transmitted to him/her by the robotic system. In special cases s/he will need to guide and direct the system, control the sensory system and maneuver the robotic system. In longer term, with better saved knowledge bases, less trained HOs will operate/navigate the robotic system.

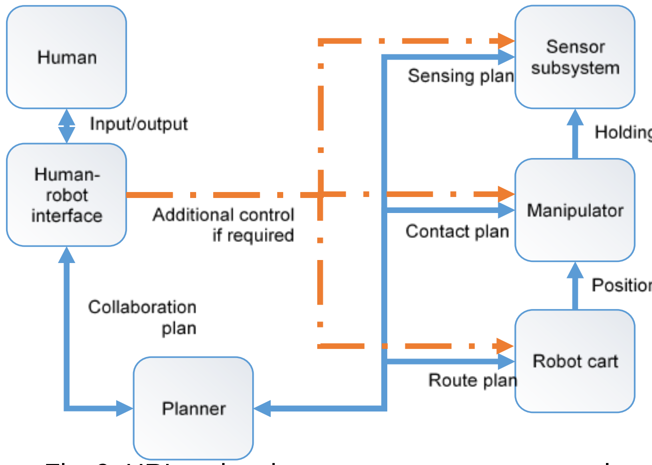

Fig. 9. HRI assisted autonomous system control block diagram.

Integrated collaboration requirement planning utilizes the hierarchical structure of subsystems to build constraints in robot task planning. The plan will control the system to execute coherently. When errors (in any system) and conflicts (with external obstacles) are detected, the new working environment will trigger an adjustment over the original plans. Hence, without having to re-plan the entire task, the robot can smoothly recover from malfunctions with/without human intervention. Optimal plans and recovery operations are stored for the Planner, as adaptive learning for future rapid planning and recovery.

2.5.1.5 Manipulator optimal sampling trajectories

Optimal sampling trajectories will be developed for sensors and the biotic/abiotic stress geometrical and kinematic characteristics. Two scenarios will be examined: 1) the origin, destination and obstacles' relative or actual coordinates and orientations are known and modeled; 2) they are unknown. In (2), several alternatives will be evaluated: Marking a destination point by a single manipulator-mounted camera, guaranteeing a direct line of sight free of obstacles and gaining only 2D target information, or evaluating 3D information. In both, target detection can be acquired by computer vision and/or a HO using the HRI and sensor systems. Optimal sampling trajectories will be calculated for the robot navigation problem in configuration space, where 3D information is known, or modified visual servoing with closed loop control, if only 2D information is given (Bechar et al.,'14a). For complex environment with multiple obstacles an RRT model will be developed. In case of several sampling points in the manipulator working envelope, the optimal sampling order will be defined. A simulation tool will be developed to simulate all scenarios and alternatives described, to study the trajectory characteristics and narrow the solutions space. Lab and field experiments will be run using Motoman NH-5L (available both at ARO and Purdue) and a co-robot (designed for safe HRI).

2.5.1.6 The robotic Platform and supporting subsystems

We will reuse two platforms already developed (ARO project #4594396) for autonomous robotic greenhouses sprayer, funded by Israel Ministry of Agriculture (Fig. 2). Both can move autonomously, steer and navigate along crop rows, including navigation, steering and locating algorithms already developed for greenhouse plots. Those will be modified to fit this project.

2.5.2. Experiments, potential pitfalls and alternatives

Optimal Sampling Trajectory Trials: Four sets of optimal sampling trajectories will be compared, using Motoman and co-robot manipulators: a) lab experiment with two scenarios, with 3D or only 2D information known. A manipulator will apply its internal sensors-based control to move. Two cameras, one mounted on the manipulator end-effector and one at fixed location in the lab will record during trials. Configuration space method for 3D cases and visual servoing for 2D cases will be used. In 2D, destination points will be determined by HO via HRI interface. b) Similar to (a), but using the sensor system developed at UMD and HRI system developed at PU to evaluate performance and integration of all sub-systems. c) Field experiment conducted at the ARL greenhouse to evaluate the performance in field conditions. d) Lab experiment to examine sampling technique with a SPAD sensor mounted on the manipulator. Similar to (a), a camera mounted on the manipulator end-effector will guide the SPAD by visual servoing, or by HRI interface, till reaching physical contact with a target leaf.

Expected pitfalls: Errors in 3D modeling and fixation of origin and destination data; lack of data to calculate the optimal trajectory in 2D scenarios; or reaching singularity in visual servoing; or with configuration space method, SPAD will not come in contact with a leaf. In these cases some of the data will be determined manually; the environment modeling of crop row and obstacles will be simplified; and a statistical SPAD sampling algorithm will be developed to ensure physical contact.

HRI Collaboration System Trials: Four experiment sets of HRI collaboration will be conducted: a) To demonstrate and evaluate HRI collaboration for optimal trajectories, using the HRI testbed and the manipulator, The experiment will be performed at ARO and PU; b) Two experiments to demonstrate and evaluate hybrid HRI algorithms for stress inspection using the HRI testbed and the sensor system. The experiments will include the objective function model and the best CL. Experiment set (b) will be performed at UMD and ARO. c) Lab and field experiment set with the HRI testbed and the sensor system to investigate and determine performance for stress and navigation. d) Comprehensive experiment set of the developed HRI system. The experiment will integrate all testbeds and developed systems to enable HRI system for greenhouse stress monitoring. In all four experiment sets, three to four CL will be tested, comprising fully autonomous robot level, manual level, and several HRI CL.

This plan will enable us to test and validate Hypothesis 2. Expected pitfalls: Lack of timely input, pace mismatch, and instability of human performance. In these situations, the trial pace will be reduced to minimize possible overloads, the problem will be simplified and the operator intervention will be limited to fewer and simpler inputs. In case of communication delays that reduce the efficiency of HRI collaboration, it will be readjusted by the integrated Planner for collaboration. Since communication is one of the critical factors of the CL to use between HO and the automated system parts, the Planner will be designed to ensure safety, backup and continuity of sensing operations.

Task Planning Trials: Three experiment sets of integrated task planning with increasing complexity will be conducted with computer simulation and with prototype HRI collaborative system: a) Use preliminary data from sensing system, manipulators, and HRI collaboration to simulate collaborative task requirement planning procedures and protocols for tasks running on the robot cart. b) Test the compatibility of integrated task Planner and HRI collaboration testbed to observe and measure the robotic system working on stress identification and locating tasks in greenhouse environment with limited human intervention; and c) Run validation experiments on the final developed system with integrated task planning for all subsystems integrated.

This plan will enable us to test and validate Hypothesis 3. Expected pitfalls: Task requirements that are issued by task Planner but cannot keep pace with a dynamically changing environment. In such cases, CL needs to be redesigned, involve more HO intervention, or reduce robot autonomy.

Integrated Image Sensing System Platform Trials: Three trials will be conducted: a) Individual tests of thermal, MSI and 3D imaging sub-systems in lab and greenhouse, for performance validation of optics, electronics and software; b) Test of the integrated imaging system in lab and greenhouse, for synchronized acquisition, multi-modality calibration, data fusion and plant stress detection with ground truth validation; and c) Test of imaging system mounted on mobile platform. This plan will enable us to test and validate Hypothesis 1. Expected pitfalls: While there are many details involved in the study, aspects to be considered are: a) Inconsistent lighting conditions -Lighting variations due to physical location, time of day, plant canopy structure, etc. can cause errors in MSI. To address it, we will install high power light sources on the robot platform, place calibration targets in selected areas, control for location and time of measurements, and utilize 3D imaging information; b) Motion induced imaging artifacts -- We will optimize parameters such as shutter speed, lens aperture, luminous power, to reduce motion blur in the images. If necessary, we can employ a skimming and scanning strategy, i.e., survey the field in mobile skimming mode, and pause the robot from time to time to take a closer look by scanning a plant in detail; c) Computation power bottleneck -- The magnitude of image data to be acquired and analyzed in real time, along with demanding navigation/planning tasks taking place at the same time may overload the computer(s) on board the platform. To address it, in addition to optimizing the processing algorithms, we can leverage GPU(s) parallel processing function, or use cloud processing. The stressed plants in the experiments will be monitored and defined by a plant pathologist for type and level of the stress and symptoms in order to have the most accurate results, both in terms of sensing and motions accuracy, and detection correctness.

3. Description of the expected results

This research addresses BARD priorities: 1) Sensors and Robotics linking biological phenomena with sensors or otherwise bridging into the field of precision agriculture and labor reduction, and 2) Increased Efficiency of Agricultural Production. It corresponds directly with the BARD primary disciplines of Agricultural Innovation and Engineering Technologies.

The expected results and impacts of this project: New knowledge and original development of an extensible human integrated robotic system prototype for early and effective biotic and abiotic stress identification and localization in greenhouse crops. It will far exceed the performance of an autonomous system, and of human inspectors. Particular anticipated discoveries that will overcome current obstacles for such a needed solution include: Integration of sensor system and sensor fusion algorithms fitted for robotic early identification and localization of biotic and abiotic stresses; using the detected information as input to knowledge-based decision making system recommending interventions such as precise spraying of pesticide, fungicide, nutrient, irrigation, etc.; HRI algorithms for inspection tasks and simulation software to control and pre-evaluate the performance and operation of a sampling manipulator; and HRI systems and testbeds that could be used as research platforms and experiments for extending to other agricultural tasks and environments.

This project will also validate experimentally the original integration of advanced technologies in multispectral agricultural sensing, human-robot collaboration, and knowledge-based collaborative planning and control. The integrated control of the robotic system will influence the design and production of many agricultural automation systems. With increased capabilities in automatic planning, learning of complex tasks, and error detection and prevention, automation systems can improve the quality and quantity of food production with reduced human labor cost.

This project and the extendible design prototype will enable the application of precision agriculture in practice. It will enable farmers to make decisions at higher resolutions and apply individual, precise treatment to reach their expected plant potential.

4. Timetable of the Work Plan

Research Tasks	Institute	Year 1	Year 2	Year 3
3.5.1.1 Development of sensor system	**UMD**			
MSI camera and lighting setup w/hardware & software	UMD			
Thermal camera setup w/ hardware and software	UMD			
3D imager setup w/hardware and software	UMD			
SAPD setup w/hardware and software	ARO			
Imaging system integration w/hardware & software	UMD			
Imaging system tests in lab and field	UMD, ARO			
Evaluation, modification and enhancement	UMD, ARO			
Hardware and software modification & improvement.	UMD			
3.5.1.2 – Data acquisition and data fusion	**UMD**			
Data acquisition	UMD			
Sensor fusion study and optimal sampling	UMD, PU, ARO			
Decision support algorithms	PU, UMD			
3.5.1.3 Prototype sensing platform	**UMD**			
Design of sensing platform	UMD, ARO, PU			
Testing and experiments	UMD, ARO			
Optimization of the sensing platform	ARO, UMD			
3.5.1.4 Human-Robot collaboration system	**PU**			
Development of collaboration levels & objective function	ARO, PU			
Development of adaptive algorithms	PU, ARO			
Testbed design	PU, ARO			
Fault-tolerant interface design	PU			
HRI collaboration for optimal trajectories experiment	ARO			
HRI stress inspection experiment	ARO, UMD			
Field experiments of HRI system	ARO, PU			
Collaboration requirements algorithms/protocols	PU			
Contact planning and control algorithms	PU, UMD			
Sensing planning and control	PU, UMD			
Integration of collaborative control Planner	PU, ARO			
Lab and field tests with Planner	PU, UMD			
Field test with integrated systems on robot cart	ARO, PU			
Modifications and improvements	ARO, PU			
3.5.1.5 Manipulator sampling trajectories	**ARO**			
Development of optimal trajectories algorithms	ARO			
Development of a simulation tool	ARO, PU			
Design the method and control for visual servoing	ARO			
Optimal trajectory lab and field experiments	ARO, PU			
3.5.1.6 Robotic Platform & supporting subsystems	**ARO**			
Modification of the robotic platforms	ARO			
Tests of the platforms	ARO			

5. Details of Cooperation

This proposal is based on strong synergistic cooperation between the Israeli and U.S. groups. Substantial expertise in vision technologies, optical sensors, pattern recognition, optics, signal analysis and processing, disease detection, collaborative control, robotics and mechanization exists at the ARO, Israel; Purdue University and University of Maryland, The US. The teams include experienced scientists from complementary engineering expertise with Dr. Bechar's background in Robotics, HRI, machine vision, biotic stress detection and automation; Dr. Nof's background in robotics, collaborative systems, conflict and error prognostics, and sensor networks; Dr. Tao's expertise in machine vision, instrumentation, spectral imaging detections, 3D imaging, machine learning; All members are experienced and had worked on joint research projects before and are well equipped to handle and deliver the planned research tasks.

Based on the holistic concept of the proposal, all project parts and components are required to be developed with regard to other parts and subsystem in order to have an optimal design of the entire system. This approach will require and manifest in a tight collaboration between all team members and institutions. As shown in the time table, most of the tasks and subtasks require the researchers to integrate their efforts and results, which will validate that the integrated technologies have actually succeeded to identify and locate the experimental types of biotic and abiotic stresses and risks. Preliminary and integrated testing and validation of progressing results will be on-going throughout the project both at each site, and together in Israel. The integration objective will guide the researchers to combine their research results for field testing, which will verify that the technologies have actually succeeded to monitor stresses symptoms, and validate the effectiveness of the overall system.

The project members will share images, and algorithms via the Internet, conference calls and through the mutual visits of the PI's at the cooperating sites. The team will set up TeamViewer to the robot's onboard PC to allow PIs (both Israel and U.S.) to simultaneously view the real-time robotic activities and data collection in the field. Specifically, the cooperation between the teams will focus mainly on four areas: (1) Algorithms and results of anomaly identification and localization in the plants done at the U.S. site at UMD will be shared with the Israeli site during the development of the approach for determination of the manipulator optimal trajectory features and constraints. (2) Approaches developed in Israel on the manipulator optimal trajectory will be shared, integrated with the HRI system and implemented at the U.S. site at Purdue University PRISM Lab. (3) the overall system will be integrated in the Israel site and tested in greenhouses of ARO. (4) The experimental results will be analyzed, documented, evaluated and prepared for dissemination. Two international trips are scheduled for this project. At the end of the second year, Dr. Bechar will travel to the U.S. to observe the results of Dr. Tao's and Dr. Nof's research to date. To provide an opportunity for intermediate technology transfer and idea sharing among the U.S. and Israel researchers, and an opportunity for extended planning toward the field experiments that are planned to occur in Israel during the third year of the project. A trip in year 3 will entail Dr. Nof / Dr. Tao traveling to Israel to test the integration of control sub-systems and oversee the field trials. This trip will also enable technology transfer as they observe the field performance of Dr. Bechar's and Dr. Tao's/Dr. Nof research.

6. Facilities

The IAE at the ARO has facilities and equipment to perform basic and applied research in the frame of the proposed project. The ARL specializes in research and development of agricultural robotic platforms and manipulators and HRI collaborative systems. Dr. Bechar's team has developed in an ongoing research a greenhouse autonomous robotic sprayer, a HRI collaborative system for selective tree pruning, a HRI melon collecting system and a robotic sonar system for yield assessment and plant status evaluation. The ARL has under its direct control a 500 m^2 greenhouse to execute some of the field experiments planned in the project and an additive manufacturing system, QubeX Trio, a '3D printer' that will be used to design and manufacture parts and interfaces required in the project. The ARL is equipped with a robotic sprayer platform and an experimental robot that will be used in the project, a 6 DOF Motoman MH-5L, a Sick Inc. LMS 110 LADAR, a Tetracam ADC lite, MSI camera that can be mounted on the manipulator, various sensors, such as US, proximity, accelerometers, compass and GPS. The facilities also include an electronics and mechanics shops and services of research greenhouses with biotic and abiotic stresses control at the ARO. An agronomist will be responsible for the supervision of greenhouse preparation and the plants with biotic and abiotic stresses. Software tools are available for algorithms development and implementation.

PRISM lab at Purdue University has led research in automation systems for more than 20 years. Its cyber resources, control and optimization software platforms, and equipment will be available for this project. Researchers at PRISM lab have innovated and delivered algorithms, software and systems for interactive and collaborative robotics. Specifically, PRISM lab developed fault-tolerant collaboration protocol for telerobot control, distributed conflict/error detection and prevention over e-Work network, demand and capacity sharing protocols, system integration modeling and control for parallel and collaborative enterprises, integrated system for multi-dimensional HRI collaboration in design and rescue, etc. The NSF-industry supported PRISM lab has multiple CAD and DSS workstations with simulation packages for task network administration, multi-agent systems, industrial/service robots, and enterprise resource planning. High performance computing resources and industrial co-robots are accessible from PRISM lab.

The Bio-imaging and Machine Lab (2,800 ft^2) at the UMD is specialized in imaging and sensing, image processing, pattern recognition, industrial automation, and medical instrumentations. The equipment and facilities available include pilot scale vision systems with specialized digital image processors; Broad spectra imaging systems including x-ray, UV, VIS and, NIR; High-speed cameras, optics, spectrophotometer, oscilloscopes and analyzers; a robotics laboratory; specialized software and utilities for algorithms design and image analysis; and a large mechanical fabrication shop with CNC milling machines and 3D printers for prototyping. The UMD campus greenhouse is in the visible distance of Dr. Tao's office window and is accessible. The UMD Shady Grove campus's greenhouse near Dr. Tao's house is also available for experimentation. UMD has a large experimental farm that can be available upon request.

7. Relevant Bibliography

ALCHANATIS, V., COHEN, Y., COHEN, S., MOLLER, M., SPRINSTIN, M., MERON, M., TSIPRIS, J., SARANGA, Y. & SELA, E. 2010. Evaluation of different approaches for estimating and mapping crop water status in cotton with thermal imaging. Precision Agriculture, 11, 27-41.

ALCHANATIS, V., RIDEL, L., HETZRONI, A. & YAROSLAVSKY, L. 2005. Weed detection in multi-spectral images of cotton fields. Computers and Electronics in Agriculture, 47, 243-260.

BAETEN, J., DONNé, K., BOEDRIJ, S., BECKERS, W. & CLAESEN, E. 2008. Autonomous fruit picking machine: A robotic apple harvester. Field and Service Robotics, 42, 531-539.

BECHAR, A. 2010. Robotics in horticultural field production. Stewart Postharvest Review, 6, 1-11.

BECHAR, A., BLOCH, V., FINKELSHTAIN, R., LEVI, S., HOFFMAN, A., EGOZI, H. & SCHMILOVITCH, Z. 2014a. Visual Servoing Methodology for Selective Tree Pruning by Human-Robot Collaborative System AgEng 2014. Zurich, Switzerland

BECHAR, A., MEYER, J. & EDAN, Y. 2009. An Objective Function to Evaluate Performance of Human-Robot Collaboration in Target Recognition Tasks. IEEE Transactions on Systems Man and Cybernetics Part C-Applications and Reviews, 39, 611-620.

BECHAR, A., NOF, S. Y. & WACHS, J. P. 2014b. Precision Collaboration and Advanced Integration Using Laser Systems and Techniques. In: NOF, S. Y. (ed.) Laser and Photonic Systems. CRC Press.

BUERLING, K., HUNSCHE, M. & NOGA, G. 2012. Presymptomatic Detection of Powdery Mildew Infection in Winter Wheat Cultivars by Laser-Induced Fluorescence. Applied Spectroscopy, 66, 1411-1419.

BURKE, J. L., MURPHY, R. R., ROGERS, E., LUMELSKY, V. J. & SCHOLTZ, J. 2004. Final report for the DARPA/NSF interdisciplinary study on human-robot interaction. IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews, 34, 103-112.

CANNING, J. R., EDWARDS, D. B. & ANDERSON, M. J. 2004. Development of a fuzzy logic controller for autonomous forest path navigation. Transactions of the Asae, 47, 301-310.

CARDOSO, A. D., RESENDE ALVARENGA, M. A., MELO, T. L., SILVEIRA VIANA, A. E. & MATSUMOTO, S. N. 2011. SPAD index in the leaves of potato under splitting and doses of nitrogen and potassium. Revista Ciencia Agronomica, 42, 159-167.

CERES, R., PONS, F. L., JIMENEZ, A. R., MARTIN, F. M. & CALDERON, L. 1998. Design and implementation of an aided fruit-harvesting robot (Agribot). Industrial Robot, 25, 337-+.

CERKAUSKAS, R. F. & BUONASSISI, A. 2003. First report of powdery mildew of greenhouse pepper caused by Leveillula taurica in British Columbia, Canada. Plant Disease, 87, 1151-1151.

CHANE, C. S., MANSOURI, A., MARZANI, F. S. & BOOCHS, F. 2013. Integration of 3D and multispectral data for cultural heritage applications: Survey and perspectives. Image and Vision Computing, 31, 91-102.

CHEN, B., TOJO, S. & WATANABE, K. 2003. Machine vision based guidance system for automatic rice transplanters. Applied Engineering in Agriculture, 19, 91-97.

CHEN, X., JING, H., TAO, Y. & CHENG, X. 2008. Real-time image analysis for nondestructive detection of metal slivers in packed food. Transactions of the ASABE, 51, 303-309.

CHENG, X., CHEN, Y. R., TAO, Y., WANG, C. Y., KIM, M. S. & LEFCOURT, A. M. 2004. A novel integrated PCA and FLD method on hyperspectral image feature extraction for cucumber chilling damage inspection. Transactions of the American Society of Agricultural Engineers, 47, 1313-1320.

COHEN, Y., ALCHANATIS, V., ZUSMAN, Y., DAR, Z., BONFIL, D. J., KARNIELI, A., ZILBERMAN, A., MOULIN, A., OSTROVSKY, V., LEVI, A., BRIKMAN, R. & SHENKER, M. 2010. Leaf nitrogen estimation in potato based on spectral data and on simulated bands of the VEN mu S satellite. Precision Agriculture, 11, 520-537.

CORP, L. A., MCMURTREY, J. E., MIDDLETON, E. M., MULCHI, C. L., CHAPPELLE, E. W. & DAUGHTRY, C. S. T. 2003. Fluorescence sensing systems: In vivo detection of biophysical variations in field corn due to nitrogen supply. Remote sensing of environment, 30. 86, 470-479.

DANDOIS, J. P. & ELLIS, E. C. 2013. High spatial resolution three-dimensional mapping of vegetation spectral dynamics using computer vision. Remote Sensing of Environment, 136, 259-276.

DAR, I., EDAN, Y. & BECHAR, A. An adaptive path classification algorithm for a pepper greenhouse sprayer. American Society of Agricultural and Biological Engineers Annual International Meeting 2011, 2011 Louisville, KY. 288-302.

DEMMEL, M. R., EHRL, M., ROTHMUND, M., SPANGLER, A. & AUERNHAMMER, H. 2002. Automated Process Data Acquisition with GPS and Standardized Communication - The Basis for Agricultural Production Traceability. ASAE Paper No. 02-3013.

ERDEM, E., HASPALAMUTGIL, K., PALAZ, C., PATOGLU, V. & URAS, T. Combining high-level causal reasoning with low-level geometric reasoning and motion planning for robotic manipulation. Proceedings - IEEE International Conference on Robotics and Automation, 2011. 4575-4581.

FRANKE, J. & MENZ, G. 2007. Multi-temporal wheat disease detection by multi-spectral remote sensing. Precision Agriculture, 8, 161-172.

GOTTSCHALK, R., BURGOS-ARTIZZU, X. P., RIBEIRO, A., PAJARES, G. & SáNCHEZ-MIRALLES, Á. Real-time image processing for the guidance of a small agricultural field inspection vehicle. 15th International Conference on Mechatronics and Machine Vision in Practice, M2VIP'08, 2008. 493-498.

GRANT, O. M., TRONINA, L., JONES, H. G. & CHAVES, M. M. 2007. Exploring thermal imaging variables for the detection of stress responses in grapevine under different irrigation regimes. Journal of Experimental Botany, 58, 815-825.

GRIEPENTROG, H. W., NORREMARK, M., NIELSEN, H. & BLACKMORE, B. S. 2005. Seed mapping of sugar beet. Precision Agriculture, 6, 157-165.

GUO, L. S. & ZHANG, Q. 2005. Wireless data fusion system for agricultural vehicle positioning. Biosystems Engineering, 91, 261-269.

HANNAN, M. W. & BURKS, T. F. Current developments in automated citrus harvesting. 2004 Ottawa, ON. 4187-4196.

HU, A. P., THOMAS, S., JENNINGS, B., MCMURRAY, G. & RAINS, G. C. Development and testing of a low-cost multi-function robotic arm for agriculture. American Society of Agricultural and Biological Engineers Annual International Meeting 2014, ASABE 2014, 2014. 4565-4574.

HUANG, J.-R., SUN, J.-Y., LIAO, H.-J. & LIU, X.-D. 2015. Detection of brown planthopper infestation based on SPAD and spectral data from rice under different rates of nitrogen fertilizer. Precision Agriculture, 16, 148-163.

JAIN, N., RAY, S. S., SINGH, J. P. & PANIGRAHY, S. 2007. Use of hyperspectral data to assess the effects of different nitrogen applications on a potato crop. Precision Agriculture, 8, 225-239.

JEONG, W. & NOF, S. Y. 2009. A collaborative sensor network middleware for automated production systems. Computers and Industrial Engineering, 57, 106-113.

KAELBLING, L. P. & LOZANO-PéREZ, T. Hierarchical task and motion planning in the now. Proceedings - IEEE International Conference on Robotics and Automation, 2011. 1470-1477.

KANG, F., WANG, H., PIERCE, F. J., ZHANG, Q. & WANG, S. 2012. Sucker detection of grapevines for targeted spray using optical sensors. Transactions of the ASABE, 55, 2007-2014.

KHOT, L. R., TANG, L., BLACKMORE, S. B. & NORREMARK, M. 2006. Navigational context recognition for an autonomous robot in a simulated tree plantation. Transactions of the Asabe, 49, 1579-1588.

KONDO, N., MONTA, M. & FUJIURA, T. 1996. Fruit harvesting robots in Japan. Advances in Space Research, 18, 181-184.

LEE, W. S., ALCHANATIS, V., YANG, C., HIRAFUJI, M., MOSHOU, D. & LI, C. 2010. Sensing technologies for precision specialty crop production. Computers and Electronics in Agriculture, 74, 2-33.

LIN, F. F., QIU, L. F., DENG, J. S., SHI, Y. Y., CHEN, L. S. & WANG, K. 2010. Investigation of SPAD meter-based indices for estimating rice nitrogen status. Computers and Electronics in Agriculture, 71, S60-S65.

LIU, L., CROWE, T. G. & ROBERGE, M. 2009. SENSOR-BASED SCOUTING ALGORITHMS FOR AUTOMATIC SAMPLING TASKS IN ROUGH AND LARGE UNSTRUCTURED AGRICULTURAL FIELDS. Transactions of the Asabe, 52, 285-294.

MAHLEIN, A. K., STEINER, U., HILLNHüTTER, C., DEHNE, H. W. & OERKE, E. C. 2012. Hyperspectral imaging for small-scale analysis of symptoms caused by different sugar beet diseases. Plant Methods, 8.

MIZRACH, A. 2008. Ultrasonic technology for quality evaluation of fresh fruit and vegetables in pre- and postharvest processes. Postharvest Biology and Technology, 48, 315-330.

MOSHOU, D., PANTAZI, X.-E., KATERIS, D. & GRAVALOS, I. 2014a. Water stress detection based on optical multisensor fusion with a least squares support vector machine classifier. Biosystems Engineering, 117, 15-22.

MOSHOU, D., PANTAZI, X. E., KATERIS, D. & GRAVALOS, I. 2014b. Water stress detection based on optical multisensor fusion with a least squares support vector machine classifier. Biosystems Engineering, 117, 15-22.

NAGASAKA, Y., UMEDA, N., KANETAI, Y., TANIWAKI, K. & SASAKI, Y. 2004. Autonomous guidance for rice transplanting using global positioning and gyroscopes. Computers and Electronics in Agriculture, 43, 223-234.

NIELSEN, M., SLAUGHTER, D. C., GLIEVER, C. & UPADHYAYA, S. Orchard and tree mapping and description using stereo vision and lidar. IV International Workshop on Computer Image Analysis in Agriculture, 3rd CIGR International Conference of Agricultural Engineering 2012 Valencia, Spain

NOF, S. Y. (ed.) 2009. Handbook of Automation: Springer.

NOF, S. Y. & CHEN, J. 2003. Assembly and disassembly: An overview and framework for cooperation requirement planning with conflict resolution. Journal of Intelligent and Robotic Systems: Theory and Applications, 37, 307-320.

NUTTER, F. W., GLEASON, M. L., JENCO, J. H. & CHRISTIANS, N. C. 1993. ASSESSING THE ACCURACY, INTRA-RATER REPEATABILITY, AND INTERRATER RELIABILITY OF DISEASE ASSESSMENT SYSTEMS. Phytopathology, 83, 806-812.

NUTTER, F. W., GUAN, J., GOTLIEB, A. R., RHODES, L. H., GRAU, C. R. & SULC, R. M. 2002. Quantifying alfalfa yield losses caused by foliar diseases in Iowa, Ohio, Wisconsin, and Vermont. Plant Disease, 86, 269-277.

NYI, N., SRIDOKCHAN, W., CHAI-ARREE, W. & SRINIVES, P. 2012. Nondestructive Measurement of Photosynthetic Pigments and Nitrogen Status in Jatropha (Jatropha curcas L.) by Chlorophyll Meter. Philippine Agricultural Scientist, 95, 139-145.

OBERTI, R., MARCHI, M., TIRELLI, P., CALCANTE, A., IRITI, M. & BORGHESE, A. N. 2014a. Automatic detection of powdery mildew on grapevine leaves by image analysis: Optimal view-angle range to increase the sensitivity. Computers and Electronics in Agriculture, 104, 1-8.

OBERTI, R., MARCHI, M., TIRELLI, P., CALCANTE, A., IRITI, M. & BORGHESE, A. N. 2014b. Automatic detection of powdery mildew on grapevine leaves by image analysis: Optimal view-angle range to increase the sensitivity. Computers and Electronics in Agriculture, 104, 1-8.

OERKE, E. C. & DEHNE, H. W. 2004. Safeguarding production—losses in major crops and the role of crop protection. Crop Protection, 23, 275-285.

OREN, Y., BECHAR, A. & EDAN, Y. 2012. Performance analysis of a human-Robot collaborative target recognition system. Robotica, 30, 813-826.

PANDA, S. S., PANIGRAHI, S. & AMES, D. P. 2010. Crop yield forecasting from remotely sensed aerial images with self-organizing maps. Transactions of the ASABE, 53, 323-338.

PARASURAMAN, R., SHERIDAN, T. B. & WICKENS, C. D. 2000. A model for types and levels of human interaction with automation. Ieee Transactions on Systems Man and Cybernetics Part a-Systems and Humans, 30, 286-297.

PORTZ, G., MOLIN, J. P. & JASPER, J. 2012. Active crop sensor to detect variability of nitrogen supply and biomass on sugarcane fields. Precision agriculture, 13, 33-44.

RACCAH, B. & FERERES, A. 2009. Plant virus transmission by insects, in Encyclopedia of Life Sciences, Chichester, UK, John Wiley & Sons, Ltd, .

RAJAN, V. N. & NOF, S. Y. 1996a. Cooperation Requirements Planning (CRP) for multiprocessors: Optimal assignment and execution planning. Journal of Intelligent and Robotic Systems: Theory and Applications, 15, 419-435.

RAJAN, V. N. & NOF, S. Y. 1996b. Minimal precedence constraints for integrated assembly and execution planning. IEEE Transactions on Robotics and Automation, 12, 175-186.

ROTBART, N., SCHMILOVITCH, Z., COHEN, Y., ALCHANATIS, V., EREL, R., IGNAT, T., SHENDEREY, C., DAG, A. & YERMIYAHU, U. 2013. Estimating olive leaf nitrogen concentration using visible and near-infrared spectral reflectance. Biosystems Engineering, 114, 426-434.

SAMMONS, P. J., FURUKAWA, T. & BULGIN, A. Autonomous pesticide spraying robot for use in a greenhouse. Proceedings of the 2005 Australasian Conference on Robotics and Automation, ACRA 2005, 2005 Sydney, NSW.

SANKARAN, S. & EHSANI, R. 2012. Detection of huanglongbing disease in citrus using fluorescence spectroscopy. Transactions of the ASABE, 55, 313-320.

SCHOR, N., BERMAN, S. & BECHAR, A. A robotic monitoring system for diseases of pepper greenhouse. ECPA, 2015 Tel-Aviv, Israel. 627-634.

SCHUELLER, J. K. 2006. CIGR Handbook of Agricultural Engineering, CIGR – The International Commission of Agricultural Engineering.

SIVARAMAN, B. & BURKS, T. F. 2006. Geometric performance indices for analysis and synthesis of manipulators for robotic harvesting. Transactions of the Asabe, 49, 1589-1597.

STENTZ, A., DIMA, C., WELLINGTON, C., HERMAN, H. & STAGER, D. 2002. A system for semi-autonomous tractor operations. Autonomous Robots, 13, 87-104.

TARRíO, P., BERNARDOS, A. M., CASAR, J. R. & BESADA, J. A. A harvesting robot for small fruit in bunches based on 3-D stereoscopic vision. Computers in Agriculture and Natural Resources - Proceedings of the 4th World Congress, 2006. 270-275.

TKACH, I., BECHAR, A. & EDAN, Y. 2011a. Switching between collaboration levels in a human-robot target recognition system. IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews, 41, 955-967.

TKACH, I., EDAN, Y. & NOF, S. Y. A framework for automatic multi-agents collaboration in target recognition tasks. 21st International Conference on Production Research: Innovation in Product and Production, ICPR 2011 - Conference Proceedings, 2011b.

VAN HENTEN, E. J., HEMMING, J., VAN TUIJL, B. A. J., KORNET, J. G., MEULEMAN, J., BONTSEMA, J. & VAN OS, E. A. 2002. An autonomous robot for harvesting cucumbers in greenhouses. Autonomous Robots, 13, 241-258.

VAN HENTEN, E. J., VAN'T SLOT, D. A., HOL, C. W. J. & VAN WILLIGENBURG, L. G. 2009. Optimal manipulator design for a cucumber harvesting robot. Computers and Electronics in Agriculture, 65, 247-257.

VELASQUEZ, J. D. & NOF, S. Y. 2009. Best-matching protocols for assembly in e-work networks. International Journal of Production Economics, 122, 508-516.

WILLIAMS, N. P., LIU, Y. & NOF, S. Y. 2003. Analysis of workflow protocol adaptability in TestLAN production systems. IIE Transactions (Institute of Industrial Engineers), 35, 965-972.

WOLFE, J., MARTHI, B. & RUSSELL, S. Combined task and motion planning for mobile manipulation. ICAPS 2010 - Proceedings of the 20th International Conference on Automated Planning and Scheduling, 2010. 254-257.

YUAN, T., LI, W., FENG, Q. & ZHANG, J. Spectral imaging for greenhouse cucumber fruit detection based on binocular stereovision. American Society of Agricultural and Biological Engineers Annual International Meeting 2010, ASABE 2010, 2010. 4371-4381.

ZHANG, J.-C., PU, R.-L., WANG, J.-H., HUANG, W.-J., YUAN, L. & LUO, J.-H. 2012. Detecting powdery mildew of winter wheat using leaf level hyperspectral measurements. Computers and Electronics in Agriculture, 85, 13-23.

ZHONG, H., NOF, S. Y. & BERMAN, S. 2015. Asynchronous cooperation requirement planning with reconfigurable end-effectors. Robotics and Computer-Integrated Manufacturing, 34, 95-104.

ZHONG, H., WACHS, J. P. & NOF, S. Y. 2013. A collaborative telerobotics network framework with hand gesture interface and conflict prevention. International Journal of Production Research, 51, 4443-4463.

8. Curriculum Vitae

AVITAL BECHAR, Head of the Agricultural Robotics Lab at the ARO.

Education

- 1993 B.Sc., Aerospace Engineering, Technion, Israel Institute of Technology, Haifa, Israel.
- 1996 M.Sc., Agricultural Engineering, Technion, Israel Institute of Technology, Haifa, Israel.
- 2006 Ph.D., Industrial Engineering and Management, Ben-Gurion University of the Negev, Beer-Sheva, Israel.

Appointments

2015 Head, Department of Production, Growing and Environmental Engineering. ARO, Israel.

2014 senior research scientist (Rank A), The Institute of Agricultural Engineering, ARO, Israel.

2011 Adjunct Professor at the School of Industrial Engineering, Purdue University

2007 senior research scientist (Rank B), The Institute of Agricultural Engineering, ARO, Israel.

2003 Research Scientist (Rank C), The Institute of Agricultural Engineering, ARO, Israel.

Relevant Publications

1. **Bechar, A**., S.Y. Nof and J.P. Wachs. (2015). A review and framework of laser-based collaboration support. Annual Reviews in Control 39: 30-45.
2. Finkelshtain, R., Y. Yovel, G. Kosa and **A. Bechar**. (2015). Detection of plant and greenhouse features using sonar sensors. Proceedings of the ECPA 2015, pp. 299-305. Tel-Aviv, Israel.
3. Bloch, V., **A. Bechar** and A. Degani. (2015). Task characterization and classification for robotic manipulator optimal design in precision agriculture. Proceedings of the ECPA 2015, pp. 313-320. Tel-Aviv, Israel.
4. Schor, N., S. Berman and **A. Bechar**. (2015). A robotic monitoring system for diseases of pepper greenhouse. Proceedings of the ECPA 2015, pp. 627-634. Tel-Aviv, Israel.
5. Oren, Y., **A. Bechar** and Y. Edan (2012). Performance Analysis of Human-Robot Collaboration in Target Recognition Tasks. Robotica 30(5): 813-826.
6. Tkach, I., **A. Bechar** and Y. Edan (2011). Switching between Collaboration Levels in a Human-Robot Target Recognition System. IEEE Transactions on Systems, Man and Cybernetics, Part C 41(6): 955-967.
7. **Bechar, A.** (2010). Automation and robotic in horticultural field production. Stewart *Postharvest Review* 6(3): 1-11. (***invited review***).
8. **Bechar, A.,** J. Meyer and Y. Edan (2009). An Objective Function to Evaluate Performance of Human-Robot Collaboration in Target Recognition Tasks. IEEE Transactions on Systems, Man and Cybernetics, Part C 39(6): 611-620.
9. **Bechar, A**. And Y. Edan. (2003). Human-robot collaboration for improved target recognition of agricultural robots. Industrial Robot 30 (5): 432-436. (Invited paper).

Other Significant Publications

1. **Bechar, A.** and M. Eben-Chaime (2014). Hand-held computers to increase accuracy and productivity in agricultural work study. *International Journal of Productivity and Performance Management* 63(2): 194-208.
2. Vitner, G. and **A. Bechar** (2011). Count-to-weight transform of pre-packed packages, a case study: an efficient implementation of the NIST Handbook 133 requirements. Biosystems Engineering 108(3): 204-210.

3. **Bechar, A.** and G. Vitner. (2009). A Weight Coefficient of Variation Based Mathematical Model to Support the Production of 'Packages Labelled by Count' in Agriculture. Biosystems Engineering 104(3): 362-368.
4. Lavi N., Y. Tadmor, A. Meir, **A. Bechar**, M. Oren-Shamir, R. Ovadia, M. Reuveni, S. Nahon, H. Shlomo, L. Chen and I. Levin (2009). Characterization of the Intense Pigment Tomato Genotype Emphasizing Targeted Fruit Metabolites and Chloroplast Biogenesis. Journal of Agricultural and Food Chemistry 57(11): 4818–4826.
5. **Bechar, A**., S. Gan-Mor and B. Ronen (2008). A Method For Increasing The Electrostatic Deposition Of Pollen And Powder. *Journal of Electrostatics* 66(7-8): 375-380.
6. **Bechar, A**., S. Yosef, S. Netanyahu and Y. Edan. (2007). Improvement of Work Methods in Tomato Greenhouses Using Simulation. *Transactions of the ASABE* 50(2): 331-338.
7. **Bechar, A**., A. Mizrach, P. E. Barreiro and S. Landah. (2005). Determination of mealiness in apples using ultrasonic measurements and comparison with destructive tests. Biosystems Engineering 91(3):329-334.

Synergistic Activities

- Associate Editor, IEEE Transactions on Automation Science and Engineering, IEEE T-ASE
- Scientific reviewer of manuscripts for 14 journals, among them: Journal of Electrostatics by Elsevier Science; Food and Bioprocess Technology: an International Journal by Springer; Industrial Robot: An International Journal and Biosystems Engineering by Emerald; Transactions of the ASABE and Applied Engineering in Agriculture by ASABE; Transactions of the SMC part A by IEEE and Robotica.
- Reviewer of BARD and BSF international funds.
- Editorial committee member of ISRN Robotics.
- Chairman of the Israeli Society of Agricultural Engineering, ISAE
- Co-founder of the Israeli Robotics Association – iROB
- Member of the CIGR, EURAGENG, IEEE SMC and R&A Societies.
- Committee member of IET-210 ASABE - Systems analysis and artificial intelligence (2000-2003); AE09 EURAGENG - intelligent automation and robotics work group (2009 to date); Scientific peer-review panel, ICT-AGRI, ERA-NET (2010) and IEEE Robotics and Automation's Technical Committee on Agricultural Robotics (2011 to date).
- Orgenizer, steering committee member, theme head, program committee member, publication chair and scientific committee member in local and international conferences on robotics and agricultural engineering (ECPA 2015, ISAE 2015, BARD workshop, ICR 2010, ICR 2013, AGENG 2012, InTech 2011, AGRISENSING 2011).

Awards

- ASAE superior paper award (1999).
- IE&M award for excellent work in industry (2006).
- INCOM09 best paper presentation award (2009).

Publications

Publication of more than 40 reviewed articles, 1 book review and 2 book chapters, more than 60 technical publications and research reports, and 50 scientific conference papers and abstracts.

Patent

Gan-Mor, S., D. Eisikowitch, B. Ronen, **A. Bechar**, and Y. Vaknin. Device for performing electrostatic pollination. Israel Patent Pending No. 137222 (2007).

Gradute Students: Graduated: 5 students; Current: 4 students.

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Professional Preparation

Technion, Haifa, Israel	Industrial & Management Engineering	B.Sc./ 1969
Technion, Haifa, Israel	Industrial & Management Engineering (Human-Machine Systems)	M.Sc./1972
University of Michigan	Industrial & Operations Engineering (Robotics & Automation)	Ph.D./1976
Lucian Blaga University of Sibiu, Romania	College of Engineering	D.H.C./2007

Appointments

- Professor, Industrial Engineering, Purdue University, 1988--. At Purdue 1977--. Director, PRISM Center (Production, Robotics, and Integration Software for Mfg. & Management) 1991--.
- Visiting Professorships: Universities in EU; Hong Kong Polytechnic; Israel; Mexico; MIT; Taiwan; UEC Tokyo, UCV Chile
- Lecturer, Assistant Professor of Management, University of Michigan, Dearborn, 1974-76.
- Member, TRB committee ABE40 Critical Transportation Infrastructure Protection, and ABE40(5) Training, Education, and Technology Transfer, 2005-11
- Technology Assistance Program (TAP), Purdue University and the State of Indiana, 1992-99.
- Corporate consultant, Scitex, Inc., and Tadiran, Ltd., Israel, 1984-86.
- Senior R&D Analyst, Manufacturing Data Systems, Inc., Ann Arbor, Michigan, 1976-77.
- Programmer and Systems Analyst, Mamram Computer Center, Israel, 1968-72.

Selected Awards

1. Most Outstanding Book in Technology and Engineering Award, Association of American Publishers for *Handbook of Industrial Robotics*, Nof, S.Y. Editor (1985)
2. Significant Accomplishments in Manufacturing Systems Award, IIE (1987)
3. Most Outstanding Reference Book in Science and Engineering Award, Association of American Publishers *International Encyclopedia of Robotics*, Dorf, R.C. and Nof, S.Y., Editors, (1988)
4. Fellow: Institute of Industrial Engineers (1991); Int. Foundation for Production Research (2013)
5. *Purdue's Book of Great Teachers* (Inaugural Group, 1999)
6. Engelberger Medal for Robotics Education (2002)
7. President-Elect, IFPR (2005-07); President, IFPR (2007-09)
8. Ourstanding Service Award, International Federation of Automatic Control, IFAC (2008).

U.S. Patents

"Fault-Tolerant Timeout Communication Protocol with Sensor Integration," U.S. Patent No. 7,636,038. S.Y. Nof, Y. Liu, W. Jeong, 12.22.2009.

"Interactive Conflict Detection and Resolution for Air and Air-Ground Traffic Control," U.S. Patent No. 8,831,864. X.W. Chen and S.Y. Nof, 9.9.2014.

"Interactive, Constraint-Network Prognostics and Diagnostics to Control Errors and Conflicts (IPDN)," U.S. Patent No. 9,009,530. X.W. Chen and S.Y. Nof, 4.14.2015

Publications **Ten most relevant to the proposed project:**

1. Chen, X.W., and **Nof**, S.Y. (2007) Error detection and prediction algorithms: Application in robotics," *Journal of Intelligent & Robotic Systems*, 48(2), 225-52.
2. **Nof** S.Y. (2007) Collaborative control theory for e-Work, e-Production, and e-Service. *Annual*

Reviews in Control. 31(2), 281-292.

3. Ko, H.S., and **Nof**, S.Y. (2010) Design of protocols for task administration in collaborative production systems. *International J. of Computers, Comm. & Control*, V(1), 91-105.
4. **Nof**, S.Y., Weiner, A.M., and Cheng, G.J. (editors; co-authors), (2014) *Laser and Photonic Systems: Design and Integration*. CRC Press.
5. Zhong, H., Wachs, J.P., and **Nof**, S.Y. (2014) Telerobot-enabled HUB-CI model for collaborative lifecycle management of design and prototyping, *Comp. in Ind.*, 65(4), 550-562.
6. **Nof,** S.Y. (Ed.; co-author), (1999) *Handbook of Industrial Robotics*, 2nd ed., Wiley, New York.
7. **Nof**, S. Y. (Ed.; co-author), (2009) *Springer Handbook of Automation,* Springer Publishers.
8. Zhong, H., **Nof,** S.Y., Berman, S. (2015) Asynchronous cooperation requirement planning with reconfigurable end-effectors, *Robot. Comput. Integr. Manuf.*, 34(8), 95–104.
9. Chen, X.W., and **Nof**, S.Y. (2012) Conflict and Error Prevention and Detection in Complex Networks, *Automatica*, 48(5), 770-778.
10. Jeong, W.T., Ko, H.S., Lim, H.J., and **Nof**, S.Y. (2013) A protocol for processing interfered data in facility sensor networks, *Int. J. of Adv. Mfg. Tech.*, DOI: 10.1007/s00170-012-4657-3.

Synergistic Impacts

- **Cross-disciplinary teaching, scholarly and service accomplishments**: Introduced and improved six lab-based courses in robotics, automation, and communication, and authored textbooks for them. Served as chair, co-chair, and scientific program committee member of over 60 international conferences, on collaborative robotics; information and communication systems in networked computing, production, transportation, service, and supply networks. Active in IFAC, IFIP, and IFPR.
- With **multi-disciplinary national and international research teams** we integrate Operations Research, systems engineering, computer science, ergonomics, and cyber technologies to achieve significantly better levels of effectiveness, sustainability and quality in distributed work and service systems. Key recent accomplishments: **TESTLAN**, client-server and LAN models of integrated, collaborative assembly-and-test networks; **FDL** and **FDL/CR**, a Facility Design Language with conflict resolution for distributed, collaborative engineering; Active protocols for collaborative e-Work and e-Service; **FTTP**, patented fault-tolerant integration protocol for distributed MEMS/Nano sensor arrays and networks; **IPDN**, patented integrated prognostics and diagnostics network-aware algorithms; **CCT**, Collaborative Control Theory implemented in multi-robot and human-robot networks, and in distributed global supply networks; **HUB-CI**, Collaboratorium Initiative for Collaborative Intelligence over HUB for massively distributed real-time decision, research, and telerobotics networks.
- **Authored, edited and co-authored** with over 450 international colleagues: 13 engineering books; over 150 articles in refereed journals; over 350 conference articles in the above areas. Through the PRISM Center Nof and his students are engaged with Purdue and international colleagues collaborating in PGRN, PRISM Global Research Network. Co-editor of 16 special journal issues on: computer-integrated production; workflow models; collaborative e-Work, and Collaboration Support Systems. Editorial board member of 12 journals over the last decade.

Major advisor for: 28 PhD, 45 MS thesis students, 15 undergraduate honor researchers, and eight post-doctoral scholars.

NAME: **Yang Tao,** Ph.D., P.E., Univ. of Maryland, College Park. ytao@umd.edu 301-405-1189

EDUCATION: Ph.D. The Pennsylvania State University, 1991
Major research area: Machine vision, Digital image processing, Automated inspection, Robotics, Artificial intelligence, and Post-harvest Automation.

M.S. University of Nebraska - Lincoln, 1988
Main research area: Expert system and Artificial intelligence.

B.S. Nanjing Institute of Technology, 1982
Major study: Computer Science & Engineering.

PROFESSIONAL EXPERIENCE:

PROFESSOR, Bioengineering & Biological Resources Engineering, Univ. of Maryland, July 2004-present
ASSOC/ASST PROFESSOR, Bio&Ag Eng, Univ. of Arkansas, 4/1996- & Univ. of Maryland, 6/2000-6/2004.

Research: Investigating technologies of machine vision and image analysis for automated inspection of biological and agricultural materials. Research projects include:

- Automated defect inspection of fruit and vegetables
- Automated Imaging sex segregation of broiler chicks.
- Automated X-ray, laser, & infrared inspections of poultry products for food safety & quality.
- Advanced Medical imaging, low-dose CT, and optical imaging.
- Various other machine vision and robotics-based automation of large-volume processes for improved food quality and safety, labor efficiency and productivity.

Teaching: Senior and graduate courses in Electronics and Instrumentation. “Instrumentation in Biosystems” including sensors, solid-state analog and digital electronics, computer interfacing and controls. “Imaging and Rapid Analysis of Biological and Agricultural Materials”, “Mechanics of Food Engineering”, “Capstone Engineering Designs”.

Advising: Supervised/ing, 9 visiting scientists, 6 post-doctorate associates, and 19 Ph.D and MS students.

Web: http://www.bioe.umd.edu/research/laboratories.html#tao http://www.bioe.umd.edu/facstaff/tao/html/research.html

VICE PRESIDENT / DIRECTOR of R & D, AGRI-TECH, Inc (FMC Corp). 1993-1996, 1991-1993

Research leader responsible for corporate R&D programs executed to automate agricultural processes. Enable technologies currently under scientific investigation and technological development including Machine vision, Digital image processing, Non-invasive inspection, High-speed optical-electronic sorting and computer based machine control systems.

Headed the research and development of award-wining (1993 ASAE AE50) advanced high-resolution Merlin® color vision sorting system for sorting a wide variety of fruit and vegetables including apples, citrus, pears, tomatoes, and stone fruits for quality grades at speed up to 44 tons/hour. Wide installations in many countries, including the U.S. (sorting about 45% of total US apples alone), Canada, South America countries, China and other countries.

Headed projects including OSCAR™ optical inspection system, Vision-robot defect sorter, and other R&D projects. Research and engineering management activities.

MERLIN® advanced vision sorting system developed by Dr. Tao (ASAE AE50 award for outstanding technology) inspections of a wide variety of fruit & vegetables including apples, peaches, pears, tomatoes, and citrus. It can sort fruits into 8 simultaneous quality grades at a speed up to 44 tons/hour. It has been widely installed in the United States, Canada, and other countries, and has dramatically improved fruit packing efficiency and quality -- with huge labor savings and high-skill job creations (sorting over 45% of total U.S. apples alone each year for the past decades).

AWARDS:

[1] Outstanding Researcher, College of Agriculture Alumni Annual Award, Univ. of Maryland, 2006.
[2] USDA Secretary Ann Veneman's Award for Excellence for increasing the efficiency, security, sustainability and profitability of the fruit and vegetable industry through applications of the technologies developed. 2003.
[3] USDA CSREES (Cooperative State Research, Education, and Extension Services) Award (for the same efforts above). 2003.
[4] 2002 Award for Excellence by Northeastern Regional Association of State Agricultural Experiment Station Directors for outstanding contributions to the Northeastern Multistate Research.
[5] Outstanding Researcher & Teacher Awards (2), College of Eng., U of Arkansas. 1998-1999-2000
[6] ASAE 1999 & 2000 Best Paper Awards (2), Trans. of ASAE. Awarded to top 2.5% of published articles
[7] ASAE 1994 Engineering Achievement of the Year - Sunkist Engineering Designer Award.
[8] ASAE 1993 AE50 award for outstanding innovation of technology in food and agriculture.

U.S. PATENTS:

[1] Tao, Y. 2003. U.S. Patent **6,610,953**. Item Defect Detection Apparatus and Method.
[2] Tao, Y. 1999. U.S. Patent **5,960,098**. Method for Identifying and Removing Defective Objects.
[3] Tao, Y. etc. 2002. U.S. Patent **6,396,938** Automated feather sexing of poultry chicks.
[4] Tao, Y. 2001. U.S. Patent **6,271,520**. Item Defect Detection Apparatus and method.
[5] Tao, Y. 1998. U.S. Patent **5,799,105**. Method for Calibrating a Color Sorting Apparatus.
[6] Tao, Y. 1998. U.S. Patent **5,732,147**. Defective Object Inspection and Separation.
[7] Tao, Y. 1994. U.S. Patent **5,339,963**. Methods and Apparatus for Sorting Objects.
[8] Tao, Y. 1996. U.S. Patent **5,533,628**. Methods for Sorting Objects Incl. Stable Color Transformatio
[9] Tao, Y. 2013. U.S. Patent Ser. *09/675,621*.Combined X-ray and Laser Imaging Techniques.
[10-11] 2 U.S. Patent/Pending Patent & PCT in apple and strawberry areas.

PROFESSION: Member of ASABE (Fellow), SPIE, IEEE, SME. BME. **BOARD**: P.E.


LaXser automated x-ray & laser imaging system developed by Tao's team that detects and rejects bone fragments in fillets for food safety (chicken fillets as in McDonalds and major restaurant chains). Capacity 14,000lbs/hr/ea. IP66 wash-down environment to the USDA sanitation standard.

SELECTED PUBLICATIONS:(limited to 5 in chronological order) - ***as Project Director or Advisor*:**

[1] Lu, Jiang, B. Zhu, and **Y. Tao**. 2010. Hyperspectral Image Classification Methods. In book: Hyperspectral Imaging for Food Quality Analysis and Control. Academic Press Elsevier Inc. ISBN: 9780123747532. Chapter 3:pp-79-98.

[2] Jiang, L., B. Zhu, Y. Luo, **Y. Tao**, and X. Cheng. 2009. 3D Surface Reconstruction and Analysis in Automated Apple Stem-end/Calyx Identification. Trans. of ASABE, Vol.52(5)1775-1784.

[3] Zhu, B., L Jiang, and **Y. Tao**. 2007. Three-Dimensional Shape Enhanced Transform for Automatic Apple Stem-End/Calyx Identification. Optical Engineering, Vol.46(01):017201.

[4] Ma, L. and **Y. Tao**. 2005. An Infrared and Laser Range Imaging System for Non-invasive Estimation of Internal Temperatures in Cooked Chicken Breasts. *Trans. of ASAE*, Vol. 48(2):681-690.

[5] Vargas, A., M. Kim, **Y. Tao**, A.M. Lefcourt, Y. Luo, Y.R. Chen, 2005. Detection of fecal contamination on cantaloupes using hyperspectral fluorescence imagery. J. of Food Engineering. Vol.70(8-2005):471-476.

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BARD Project Budget Summary
(in US dollars)

Principal Investigator (PI): Bechar
Affiliated Institution: Agricultural Research Organization (ARO, Volcani Center)

Budget Item	First Year	Second Year	Third Year	Total
1. Salaries and Social Benefits	15,000	18,000	18,000	51,000
2. Non Expendable Equipment	8,000			8,000
3. Operating Expenses	10,000	10,000	10,000	30,000
4. Foreign Travel		5,000		5,000
Total Direct Costs	33,000	33,000	28,000	94,000
5. Overhead Expenses	6,600	6,600	5,600	18,800
Annual Totals	39,600	39,600	33,600	112,800

BARD Project Budget Summary
(in US dollars)

Principal Investigator (PI): Nof
Affiliated Institution: Purdue University

Budget Item	First Year	Second Year	Third Year	Total
1. Salaries and Social Benefits	22,680	23,080	23,480	69,240
2. Non Expendable Equipment	9,500			9,500
3. Operating Expenses	3,140	3,140	3,150	9,430
4. Foreign Travel			6,000	6,000
Total Direct Costs	35,320	26,220	32,630	94,170
5. Overhead Expenses	7,064	5,244	6,525	18,833
Annual Totals	42,384	31,464	39,155	113,003

BARD Project Budget Summary
(in US dollars)

Principal Investigator (PI): Tao
Affiliated Institution: University of Maryland

Budget Item	First Year	Second Year	Third Year	Total
1. Salaries and Social Benefits	21,800	21,800	15,000	58,600
2. Non Expendable Equipment	10,000	10,000	2,000	22,000
3. Operating Expenses	4,870	4,030	4,670	13,570
4. Foreign Travel				
Total Direct Costs	36,670	35,830	21,670	94,170
5. Overhead Expenses	7,330	7,170	4,330	18,830
Annual Totals	44,000	43,000	26,000	113,000

BARD Project Budget Summary

(in US dollars)

Principal Investigator (PI):Avital Bechar

Affiliated Institution: ARO, Min. Ag.

Budget Item	First Year		Second Year		Third Year		Total		Total
	IS	US	IS	US	IS	US	IS	US	Project
1. Salaries and Social Benefits	15,000	44,480	18,000	44,880	18,000	38,480	51,000	127,840	178,840
2. Non Expendable Equipment	8,000	19,500		10,000		2,000	8,000	31,500	39,500
3. Operating Expenses	10,000	8,010	10,000	7,170	10,000	7,820	30,000	23,000	53,000
4. Foreign Travel			5,000			6,000	5,000	6,000	11,000
Total Direct Costs	33,000	71,990	33,000	62,050	28,000	54,300	94,000	188,340	282,340
5. Overhead Expenses	6,600	14,394	6,600	12,414	5,600	10,855	18,800	37,663	56,463
Annual Totals	39,600	86,384	39,600	74,464	33,600	65,155	112,800	226,003	338,803

9.2 Description of the budget

<u>Avital Bechar, ARO</u>

Salaries: Funds have been requested to cover the effort of the following personnel over the 3 year period. A graduate student will participate in this project for 3 years, a part time technician or engineer will participate in this project in years 2 and 3. In addition, agronomist will support the greenhouse, the plants and the experiments at 20% for 3 years.

Non-Expendable Equipment: Funds for non-expandable equipment have been budgeted at the level of $8,000 in year 1. These funds will be used to purchase the necessary equipment and related software for the optimal trajectory part such as stereoscopic camera or TOF cameras, a SPAD device and for the HR system such as touch screen or other interfaces.

Operating Expenses: Funds for operating expenses, software updates, parts, greenhouse and shop maintenance and materials required for the modification of the platforms, development of the systems, tesbeds and conducting the experiments. The operating expanses consists greenhouses and plant management.

Foreign Travel: We have requested $5,000 in year 2 of this effort to support the travel of the research personnel to our foreign collaborating partners: Purdue University and the University of Maryland.

Overhead Expenses: In accordance with the program guidelines, overhead has been limited to 20% of the total direct costs.

<u>Shimon Y. Nof, Purdue University</u>

Salaries: Funds have been requested to cover the effort of the following personnel over the 3 year period. Graduate Student: A Graduate Research Assistant (9 months effort) will participate in this project. The salary is based upon the current FY15 salary established in the school of Industrial Engineering. The student is budgeted at 50% effort in years 1 through 3

Graduate Fee Remissions is estimated $7,695, 7,795, 7,896 for year 1, 2, 3 of the project. Graduate Fee Remissions are considered part of the compensation package for all graduate students while in attendance

Fringe Benefits: Health benefits have been estimated for the student at 8.8%.

Non-Expendable Equipment: Funds for non-expandable equipment have been budgeted at the level of $9.5K in year 1. These funds will be used with funds from other (non-BARD) projects to purchase the necessary co-robot hardware and software designed for safe HRI.

Operating Expenses: Funds for operating expenses and materials have been budgeted at $3,143 per year. These funds will support expenses related to domestic travel of the research personnel to our domestic collaborating institution, University of Maryland. It will also be used to cover the cost of expendables such as software licenses and control interface hardware supplies/services for the planned robot lab experiments.

Foreign Travel: We have requested $6,000 in year 3 of this effort to support the travel of the research personnel to our foreign collaborating partner - Volcani Center, ARO, Israel Ministry of Agriculture.

Overhead Expenses: In accordance with the program guidelines, overhead has been limited to 20% of the total direct costs.

Yang Tao, UMD

Salaries: Funds have been requested to cover the effort of the following personnel over the 3 year period. Graduate Student: A Graduate Research Assistant (9 months effort) will participate in this project. The salary is based upon the current FY14 salary scale in the A. James Clark School of Engineering. The student is budgeted at 75% effort in years 1 and 2, and 50% effort in year 3. An escalation rate of 3% has been applied to the salary in years 2 and 3.

Fringe Benefits: Health benefits have been estimated for the student at 25%. Because of the varying costs for different programs and employee benefits selections, the University does not provide a single benefit rate. Benefits charged to the award will be actual costs. Tuition remission for one graduate student will be paid from this project. Tuition is estimated at 6 credits ($573 per credit hour) in year 1 and at the dissertation rate ($947 per semester) in years 2 and 3.

Non-Expendable Equipment: Funds for non-expandable equipment have been budgeted at the level of $10K in year 1, $10K in year 2, and $2K for year 3. These funds will be used to purchase the necessary cameras, optics, light source and vision processing hardware and related software.

Operating Expenses, Materials: Funds for operating expenses and materials have been budgeted at the level of $4,800, $4,000 and $4,600 for the years 1, 2 and 3 respectively. These funds will support expenses related to travel of the research personnel to our domestic collaborating institution, Purdue University. It will also be used to cover the cost of expendables such as plant samples and shop supplies/services.

Overhead Expenses: In accordance with the program guidelines, overhead has been limited to 20% of the total direct costs.