# **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.

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| HRI  Collaborative task requirement planning  Optimal route sensing & data fusion  Robot arm manipulation |
| Fig. 1: Proposed human-collaborative autonomous robotic inspection system. (See Sec. 2.5.1. for details). |

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).

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 sensing system and algorithms to monitor biotic and abiotic stresses in plants. This will be achieved by detecting early deviations in plant status and anomalies.
2. HRI collaboration algorithms to cope with the dynamic and unpredictable nature of the environment, including development of CL, adaptive, and learning algorithms.
3. Trajectory and approach algorithms for a robotic arm, required for precise visual contact.
4. Integrated task Planner 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.

The outcome 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***

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| a  b  c |
| 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. |

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).

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.

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| 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.

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| **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).

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| **Equip. cost, K$** | **Fitable for robot** | **Precision** | **Detection Earliness** | **Software, Algorithm** | **Field use** | **Where** | **System type** |
| 2-5 | Maybe | Medium to high | Medium to advanced | Filtering, Statistical analysis, LDA, PCA, PLS, | Maybe | Lab | Multi-spectral Reflectance Spectrophoometer |
| 5-20 | Maybe | High | Early: 2nd day | fluorescence amplitude ratios, mean lifetimes | Maybe | Lab | Laser UV Induced Fluore. *(Buerling et al.,'12)* |
| 10-30 | yes | Medium- High | Early | SAS, image correction, fluorescence ratios and edge detection. | yes | Lab | Laser UV Induced Fluore. Imaging Flurometer) with CCD Camera |
| 6-16 | Yes | Medium | Medium to advanced | Spatio-temporal analysis,MTMF,NDVI | yes | Field | HSI,MSI, *(Franke & Menz,'07)* |
| 3-10 | Yes | Medium | Medium to advanced | CWA, MLR, PLSR | yes | Lab | HIS (UV/VNIR *(Zhang et al.,'12)* Spectroradiometer) |
| 6-16 | Yes | High | Medium to advanced | Discriminant functions: PPV,NPV, RIR Specificity,REIP,. | yes | Greenhouse, Field | HSI, spectrometer ,*(Oberti et al.,'14b)* |
| 1-3 | Maybe | Medium / high. | \* | Optical index, TCARI), PLSR. | yes | Field | Spect. Reflectance with Halogen Light.  (Cohen et al.,'10) |
| 2-5 | Yes | High | \* | Regression models. | yes | Lab | SPAD (Nyi et al.,'12) |
| 2-16 | Maybe | Low/ medium | \* | PCA, ANOVA. regression, indices at 750 & 710 nm. | yes | Field | HS Reflectance SpectroRadiometer  (Jain et al.,'07) |
| 4-10 | Yes | Medium / high | \* | PLSR, LTCAL software. | yes | Field | SpectralReflectance with Halogen Light Fiber-Optics Probe (Rotbart et al.,'13) |
| 1-5 | Maybe | Unknown | \* | NDVI / NDRE, statistics. Crop/soil reflectance at 670, 730 & 780 nm. | yes | Field | Spectral Reflectance RapidSCAN CS-45 Portable Sensor |
| 30 | Maybe |  | Early/  medium | Image processing | yes | Field | Thermal imaging system (Alchanatis et al.,'10) |

\* 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.

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| 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 ChlorophyIl 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 (I2S2) 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.

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| 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 TeamViewerTM, 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.

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