PROJECT ACTIVITY II

I. Title

Machine Vision Based Smart Electronic Board Software System Development for Future Learning Spaces

II. Abstract

In this project, we propose a machine vision based smart Electronic Board System (EBS) for future learning spaces, which is capable of acting as a reusable writing surface where text, diagrams, images and/or drawings can be created, displayed, and erased. Particularly, we will design a real-time, hand tracking algorithm for writing and/or drawing support in flat surface utilizing multi-cameras, recognize dynamic hand gestures for user interaction and control of the proposed smart electronic board system, and detect & classify relevant/irrelevant motion regarding the operations of the proposed smart electronic board system. Additional features of the proposed system also includes a screen recording application, with enabled audio noise filtering, multimedia playback, and basic IoT (internet of things) platform support – data collection, messaging, & identity management features. The proposed system will be evaluated initially by modular processes – hand tracking for writing (via precision plot), hand gesture recognition for control (via accuracy and confusion matrix), motion detection and classification (via accuracy and confusion matrix), and other proposed features. Finally, the proposed smart electronic board system integration will be assessed using the standard system usability scale composed of 10 template questions placed next to the Likert scale, where the target system score is 80.3 or higher.

III. Introduction

Machine vision and machine learning has found its way into several modern applications, e.g. intelligent vehicles (Ranft, 2016), medical diagnosis (Thevenot, 2017), agriculture (Ball, 2017), food evaluation (Sun, 2016), human-computer interaction (Rautaray, 2015) and even in the traditional classroom (Lin, 2018) for detection of a hand-raising gesture. In the proposed project, we are going to develop and apply machine vision and machine learning algorithms to redesign/innovate the century-old blackboard technology.

After a few centuries, a chalk-based blackboard classroom is still prevalent across the world, not only in developing countries, but also in developed ones. However, a few studies highlight the harmful effects of chalk dust (even when anti-dust chalk is used) to the health (Lin, 2015; Szász, 2017; Zhang, 2018), posing various respiratory diseases and other related risks to the teacher and students in the traditional classroom setting. Although some alternatives as the marker-based whiteboard classroom appeared, this has plenty of disadvantages as well, i.e. environmental impact (due to non-biodegradable markers), pungent odor, cumbersome marker refill, and so on. Furthermore, the advent of digital native learners is a serious issue that our modern educational system is currently addressing, and the traditional classroom is repeatedly under scrutiny. Thus, there is a need for project and development focused on the learning spaces of the future smart cities.

Statement of the Problem/Objectives

In the proposed study, the goal is to design and develop a machine vision-based smart electronic board system capable of acting as a reusable writing surface where text, diagrams, images and/or drawings can be created, displayed, and erased. In other words, the proposed system is a realization of an electronic, medium-sized, dust-free, ink-free, vision-based, blackboard/whiteboard for teaching and presentations, with the following specific objectives:

- To be able to design a real-time hand tracking algorithm for writing and/or drawing support in a flat surface utilizing multi-cameras (multiple point of views) and display .
- To be able to recognize dynamic hand gestures for user interaction and control of the proposed smart electronic board system.
- To be able to detect and classify relevant vs. irrelevant motion regarding the operations of the proposed smart electronic board system.
- To develop a screen recording application, with enabled audio and noise filtering for the proposed system.
- To develop a multimedia playback service – both audio and video – for the proposed system.

- To be able to implement basic IoT (internet of things) platform support – data collection, messaging, and identity management features – for the proposed system.
- To be able to evaluate the proposed system initially by modular processes – hand tracking for writing (via precision plot), hand gesture recognition for control (via accuracy and confusion matrix), motion detection and classification (via accuracy and confusion matrix), and its proposed features. Then, the proposed smart electronic board system integration will be assessed using the system usability scale (SUS) (Lewis, 2018).

IV. Theoretical Framework

Machine vision systems analyze images from cameras to generate image feature data that guides robotic and/or automation machines in their understanding of the physical world (Corke, 2017). Machine vision is closely related to the following fields – artificial intelligence, signal processing, imaging, graphics, cognitive science, image processing, and robotics, as shown in Fig. 1.

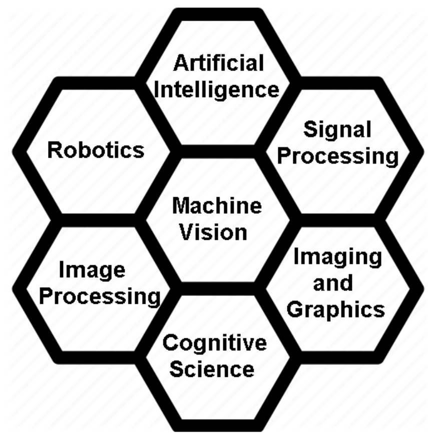

Figure 1. Machine Vision and Related Fields

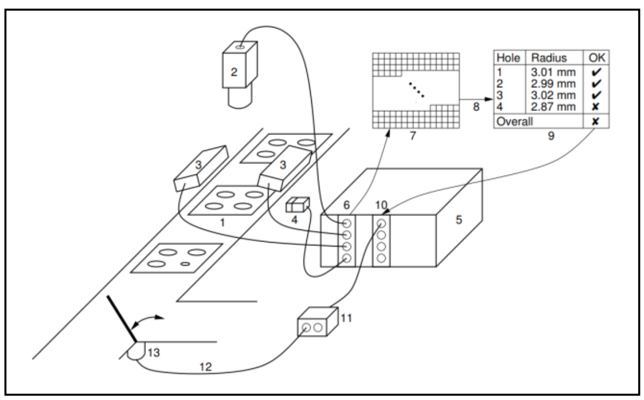

Figure 2. Machine Vision System (Steger, 2018)

Machine vision typically deals with engineering systems, e.g. machines or production lines that can perform quality inspections in order to remove defective products from production. It is a popular technology in manufacturing due to the increasing demands on the documentation of quality of products. Fig. 2 illustrates an example of a typical machine vision system (Steger, 2018). The components of a typical machine vision system includes the following: (1) an image/scene of the object for evaluation is acquired by a camera (2). The object is illuminated by the illumination (3). A photoelectric sensor (4) triggers the image acquisition. A computer (5) acquires the image through a camera–computer interface (6), in this case a frame grabber. The photoelectric sensor is connected to the frame grabber. The frame grabber triggers the strobe illumination. A device driver assembles the image (7) in the memory of the computer. The machine vision software (8) inspects the objects and returns an evaluation of the objects (9). The result of the evaluation is communicated to a PLC (11) via a digital I/O interface (10). The programmable logic controller (PLC) controls an actuator (13) through a fieldbus interface (12). The actuator, e.g., an electric motor, moves a diverter that is used to remove defective objects from the production line. Thus, as illustrated by its various components, a machine vision system is inherently multidisciplinary, e.g. electronics engineering, mechanical engineering, electrical engineering, optical engineering, and software engineering.

V. Methodology

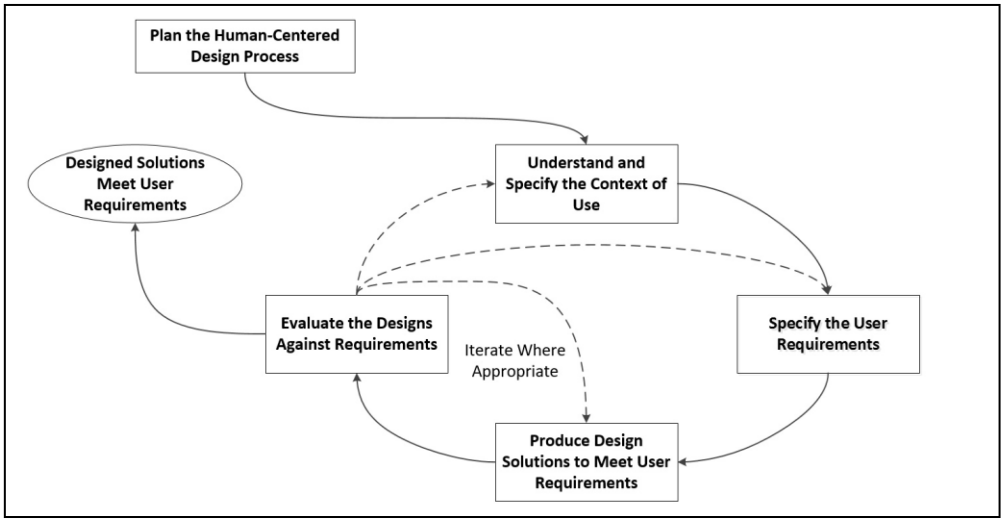

Figure 3. Human-Centered System Development Methodology (adapted from (Harte, 2017))

In this project, we adapted human-centered methodology (Fig. 3) to make sure that the needs of the user are addressed all throughout the design process, while sustaining a rapid pace of prototyping and development. The adapted methodology (Harte, 2017) is primarily composed of three phases – First Phase emphasizes the construction of a use case document that details the context of utilization of the system through storyboarding, paper prototypes, and mock-ups in conjunction with interviews of domain experts and users; Second Phase focuses on the use of expert usability inspections such as heuristic evaluations and cognitive walkthroughs with small multidisciplinary groups to review the prototypes born out of the Phase 1 feedback; and finally, the Third Phase 3 involves the classical user testing with target end users, using system usability scores to measure the usability and improve the final prototypes.

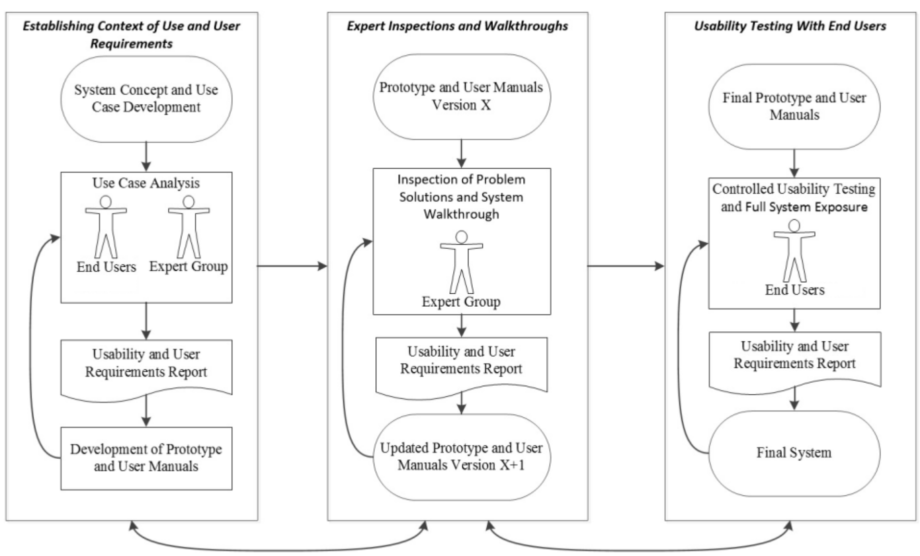

Figure 3. Adapted Human-Centered System Development for Vision Based Smart Electronic Board System Development
Note: the End Users in this case are presenters – whether a teacher or a student, while the Expert Group may include senior faculties/teachers and educators.

The adapted project and development methodology satisfies the following requirements (Harte, 2017):

Requirement 1: The design is based upon an explicit understanding of users, tasks, and environments.

Requirement 2: Users are involved throughout the design and development.

Requirement 3: The design is driven and refined by user-centered evaluation with measurable results.

Requirement 4: The process is iterative, thus, the process can revert to a previous phase if necessary.

Requirement 5: The design addresses the user experience.

Requirement 6: It includes multidisciplinary skills and perspectives.

Requirement 7: Follow the steps outlined in ISO 9241-210 and provide details of suggested activities and their expected outcomes within each phase. The ISO 9241-210 standard defines human-centered design as "*an approach to systems design and development that aims to make interactive systems more usable by focusing on the use of the system and applying human factors/ergonomics and usability knowledge and techniques*."

Requirement 8: Perform rapid prototyping, development, and testing while maintaining clear structure.

Requirement 9: Observe proper documentation of all activities, outcomes, design, and developments.

- **Prototyping (Design Set-up) Set-up and Data collection**

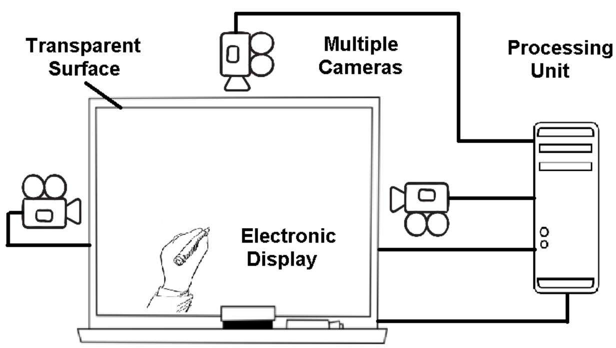

Figure 4. Proposed Machine Vision Based Smart Electronic Board System Diagram

The proposed system is composed of the following main components (Fig. 4): (a) transparent surface where the user writes or draws, which is monitored by (b) multiple cameras, that feeds video information to the (c) processing unit, that processes the synchronized inputs for hand tracking, hand gesture recognition, motion detection and classification, and outputs the result in the electronic display, e.g. LCD monitor, Projector, or any LED based display.

To the best of our knowledge, there is no existing dataset that specifically focuses on multi-view hand pose for writing/control on a flat surface. Thus, a dataset composed of at least 10000 image frames taken from at least 30 distinct people will be gathered for various poses and writing patterns, e.g. vertical, horizontal, and circular stroke patterns. A similar dataset will be gathered for hand gesture, which may be augmented with existing dataset since hand gesture recognition is a popular topic.

- **Desired Output**

When used as a teaching tool, the proposed machine vision-based smart electronic board system mimics the capabilities of the traditional blackboard where the user can do the following:

(a) Write text and draw diagrams by utilizing the user's hand gestures on the flat surface of the board system which is simultaneously shown by the electronic display (Fig. 4),

(b) Utilize erase mode to delete a portion or all the writings on the electronic board by hand, and

(c) Record via screen capture the writing session for further editing, archiving, and lecture/presentation distribution to students and other stakeholders

- **Deep Learning based Hand Gesture Recognition**

Deep learning, a subset of machine learning, involves the utilization of computational models with multiple (deep) processing layers to learn representations of data (LeCun et al., 2015). Deep learning has been applied to big data analytics (Najafabadi et al., 2015), transportation (Huval et al., 2015), robotics (Levine et al., 2015), biomedicine (Mamoshina, 2016), health informatics (Cheng et al., 2016), and other relevant fields. Deep learning has been applied to hand recognition problem, e.g. American Sign Language (ASL) hand gesture recognition (Oyedotun, 2017), hand gesture recognition on skeletal data (Devineau, 2018), and other applications (Xing 2018; Nuzzi, 2018). However, the uniqueness of our problem includes the camera orientation and multimodal input but the general algorithm process for supervised learning applies. The proposed project will follow the supervised learning framework where a generic model is learned from a labeled dataset for the purpose of detection or classification. The learning phase involves data collection, preprocessing, feature extraction (optional), and the implementation of the machine learning algorithm which usually includes training, validation, and testing. The classification/detection phase follows similar processes as in the learning phase but with a new data subjected to the trained machine learning model. The overall process is depicted in Fig. 5.

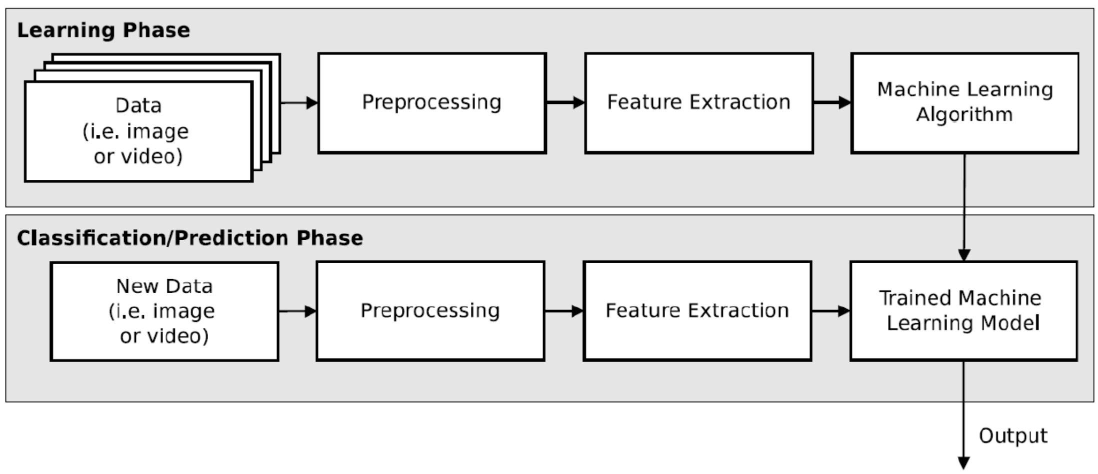

Figure 5. General Supervised Machine Learning Flow Applied to Hand Gesture Recognition

- **Evaluation Metrics**

1. *Precision plot* – This evaluation metric will be utilized for finger tracking. It computes the Euclidean center location error between the tracked finger frame-by-frame locations versus the labeled ground truth. The percentage of frames in which the estimated locations are within a given threshold distance of the ground truth positions.

2. *Classification Accuracy and Confusion Matrix* – A confusion matrix is square matrix, where the side is the number of classes being predicted. This evaluation metric will be utilized for hand gesture recognition and motion detection. We can derive the following values from the confusion matrix - accuracy or the proportion of the total number of predictions that were correct, precision or the proportion of positive cases that were correctly identified, negative predictive value or the proportion of negative cases that were correctly identified, sensitivity or recall which is the proportion of actual positive cases which are correctly identified, and specificity or the proportion of actual negative cases which are correctly identified.

3. *System Usability Scale (SUS)* – The integrated system will be tested in terms of the standard system usability scale, which is a 10 item Likert scale giving an assessment of usability. SUS has become an industry standard, with references in over 1300 articles and publications. The noted benefits of using SUS include the ff. – (a) a very easy scale to administer to participants, (b) can be used on small sample sizes with reliable results, (c) Is valid – it can effectively differentiate between usable and unusable systems The SUS questionnaire is shown in the next page.

System Usability Scale

	Strongly disagree				Strongly agree
1. I think that I would like to use this system frequently	1	2	3	4	5
2. I found the system unnecessarily complex	1	2	3	4	5
3. I thought the system was easy to use	1	2	3	4	5
4. I think that I would need the support of a technical person to be able to use this system	1	2	3	4	5
5. I found the various functions in this system were well integrated	1	2	3	4	5
6. I thought there was too much inconsistency in this system	1	2	3	4	5
7. I would imagine that most people would learn to use this system very quickly	1	2	3	4	5
8. I found the system very cumbersome to use	1	2	3	4	5
9. I felt very confident using the system	1	2	3	4	5
10. I needed to learn a lot of things before I could get going with this system	1	2	3	4	5

SUS yields a single number representing a composite measure of the overall usability of the system being studied. Note that scores for individual items are not meaningful on their own. To calculate the SUS score, first sum the score contributions from each item. Each item's score contribution will range from 0 to 4. For items 1,3,5,7,and 9 the score contribution is the scale position minus 1. For items 2,4,6,8 and 10, the contribution is 5 minus the scale position. Multiply the sum of the scores by 2.5 to obtain the overall value of SU.

SUS scores have a range of 0 to 100

System Usability Scale

	Strongly disagree 1	2	3	4	Strongly agree 5	
1. I think that I would like to use this system frequently					√	4
2. I found the system unnecessarily complex				√		1
3. I thought the system was easy to use		√				1
4. I think that I would need the support of a technical person to be able to use this system	√					4
5. I found the various functions in this system were well integrated		√				1
6. I thought there was too much inconsistency in this system			√			2
7. I would imagine that most people would learn to use this system very quickly		√				1
8. I found the system very cumbersome to use				√		1
9. I felt very confident using the system					√	4
10. I needed to learn a lot of things before I could get going with this system		√				3

Total score = 22

SUS Score = 22 *22.5 = 55

VI. References

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