OPTIMIZATION OF DYNAMIC ISSUES FOR EFFICIENT INSPECTION THROUGH MVI SYSTEM

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Abstract: Machine vision system (MVI) cope with many uncertainty from different sources as a result the actual response may be deviate. This proposed research identifies several such sources and introduces a unique methods for reducing uncertainty during the process of investigation. The suggested model present a complete machine vision inspection system which includes an agent based algorithm for minimizing the uncertain effect at the processed signal. Here, an uncertainty in the effect of improper sensor reading due to change in illumination, object distance variation from camera point and other environmental effects. The MVI system presented here is capable for inspection of any types of an object with minimal error. In experimental point of view, implementation of sensors for uncertain dynamic effects at inspection stage is optimized. The proposed sensor based configuration has been validated through simulations and implemented for effective inspection.

Index Terms - MVI system, Illumination, Sensors, Uncertain effect

I. INTRODUCTION

During the process of investigation some constraints like environmental temperature, improper illumination, Base vibration, dust and dirt etc., which plays an important role in order to variation of actual detected signal through camera. Hence, in dynamic multi-object environment a sensory arrangement can offer independent signal processing and analysis platform for an efficient inspection of an object. Due to nature of object's position the inspection environment is jumbled objects which leads to prevent the target viewing for a specific interval. Online planning may be followed for configuring the sensory arrangement dynamically [1]. Such arrangement depends on vibrant choice of (a) Sensors aimed at each object plus (b) optimum position and coordination of the sensors [2].

Sensor Pre-arrangement for Vibrant situations

Generally Sensor implementation founded on assignment restrictions over distributed sensor arrangements [3] and also based on analytical procedure by considering task requirement with sensor parameters [4]. Data acquisition and analysis for single object generally follows offline approaches while in case of multi object dynamic environment an attention based behavior [5-7] can used. This system is responsible for selection of single target and at the same instance entire sensors are focused for specified interval. As a result dropping the single and multi-object environs problem. In contrast, the proposed model facilitate individual camera to record the different objects as per their predictable outcomes so as to exploit their efficiency. Again the sensory arrangement planned here is skillful for online sensor re-configuration intended for automatic inspection in vibrant environment. Now a days an agent based methods has proposed for the online sensor planning so as to minimizing inspection difficulty. [8-14].
Here an agent based scheme is adopted for selection of sensor as well as locating in multiple object atmosphere. As a result the dynamic effect is optimized and increase the system's throughput.

II. SENSOR PLANNING FOR OBJECT RECOGNITION

Here the dynamic environment include multi-objects moves through inspection bed and a sensing arrangement is planned by considering the number of objects, degree of freedom , and viewing angle etc. Due to use of an agent based planning scheme, the dynamic issues are reduced and the system's performance is also increased. Generally in MVI system the vision cameras are adjusted in terms of alignment as well as optical factors but they are unable to fuse data from multi-cameras. But, the proposed work dynamically adjustment is possible by considering the camera position and data fusion. During the course of sensor arrangement reorientation, sensor dispatching maximizes the system effectiveness by animatedly choosing the exact sensors to acts on each object as well as decide their best positions. Assuming the demand instants (System constraints or user defined) as T_i the location of each object at specific instant is determined by considering their motion. For a nth sensor acting on j^{th} demand instant, the visibility measure can be expressed as $V_{jn} = \begin{cases} W_k U_k f(\theta), & if \quad unoccluded \quad demand \quad po\text{int} \\ 0, & Otherwise \end{cases}$

Where W_k is user defined weight, U_k is the weight assigned by system serviced by sensor. Due to this the MVI system's performance has increased. The proposed MVI structure comprises of multi-sensor -agents, a referee-agent and a judge-agent. The sensor-agent is monitored and enforced by two virtual agents. During sensor disappointment the system wants to eliminate the linked sensor-agent. The sensor -agent is accountable for selecting demand instant for object detection by an associated sensor and optimizing pose so as to maximizing sensor's performance. In a three demand instant limit [2 0 3] combination referring to servicing target or object 2 at request-period-1. This grouping is calculated by considering exhaustive search of all conceivable combinations. If entire search galaxy for a sensor-agent is $(t+1)^n$, here t is the aggregate number of non-recognized objects and n is the number of demand -instants. Hence entire search-space for the whole system is equal to $S(t+1)^n$, where S is the whole sensor numbers. Similarly for a unified supervisor the search space is $S(t+1)^{n.s}$. At every steps of investigation the sensor-agent identifies the best position for an individual sensing element. Using optimal sensor poses and object's positions the sensor-agent determines the predictable possible visibility for respective grouping and then estimates all groupings examined to regulate acceptable results.

One Sensor Visibility Performance

Considering a region of interest (R) for a specific area (A) accessed by $'n'$ sensor as represent in figure-1, where Ev_i be an event in which an object is focused at L and visible. The possibility of vision by any one sensor is expressed as $P(\bigcup_{i=1}^{n} E_{Vi}$. Again it is expanded as

$$P(\bigcup_{i=1}^{n} E_{Vi}) = \sum P(E_{Vi}) - \sum P(E_{Vi},1,E_{Vj}) + \dots\dots\dots + (-1)^{n+1} P(I_i E_{Vi}) \cdot \quad (1)$$

The projection of an object in certain direction can be calculated in a useful manner by considering r as the average maximum distance from centroid to projected object points at different directions. Generally in cylinders, r is the radius; for square prism with side 2s, $r = \frac{1}{\pi/4}\int_0^{\pi/4} s\cos\theta\, d\theta = 2\sqrt{2s}/\pi$. The quantity r will be useful in manipulative the average occluding region of an object. Moreover, it can effortlessly be exposed that, the distance d_i for an object obstructed to other object is related to its distance D_i from sensor i [Figure-1 (b)].

Statistically, $d_i = \left(D_i - d_i\right)\mu_i = D_i \frac{\mu_i}{\mu_i + 1}$, and $\mu_i = \frac{h}{H_i}$ (2)

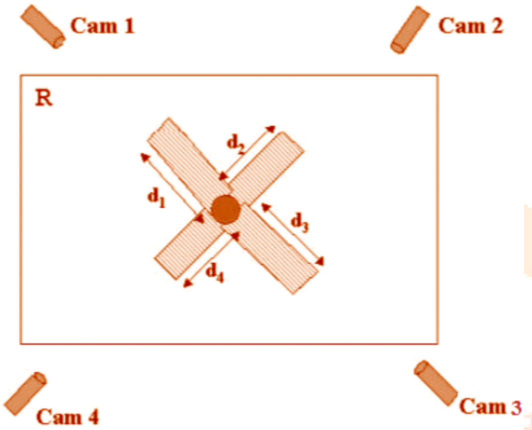


Figure-1 : (a) Camera positioning.

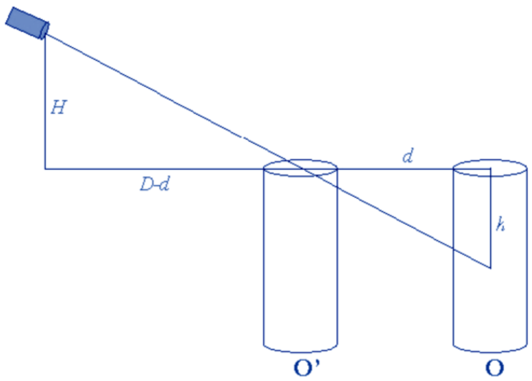


Figure-1: (b) Position mismatch condition by an object with respect to distance variation

Considering an objects has a certain density of possession and there is no non-uniform densities, with increase in K-objects along with area A uniformly such that $k = \lambda A$. (3)

In continuous object densities λ is expected. Now $P(\bigcap_{i\in(i_1,i_2,\dots,i_m)} E_i) = \lim_{k\to\infty}\prod_{j=0}^{k-1}\left(1 - \frac{A^o_{(i_1,i_2,\dots\dots i_m)}}{k/\lambda - jA_{ob}}\right)$ (4)

Here, $a = \frac{1}{\lambda A^o_{i_{1,\dots\dots} i_m}}$, $b = \frac{A_{ob}}{A^o_{i_{1,\dots\dots} i_m}}$, '$a$' is conformation of object location and 'b' is a correction of object location *for* finite object size. Hence

$$P(\bigcap_{i\in(i_{1,}\dots\dots i_m)} E_i) = \lim_{k\to\infty}\prod_{j=0}^{k-1}\left(1 - \frac{1}{ka - jb}\right) \quad (5)$$

Unequal Object Mass

For unequal object mass, to progress the design $\left(j+1\right)^{th}$ object has a region existing to it is R minus the region employed by the j previous objects. This object is situated in "available" region corresponding to the density function $'\lambda'$. The probability for object to be present in the occlusion region is $R^o_{\left(i_1,i_2,\dots\dots i_m\right)}$ and then be determined as the ratio of an object present in occlusion region and object located in available region. Thus, it can be written as

$$P(\bigcap_{i\in(i_1,i_2,\dots,i_m)} E_i) = \lim_{k\to\infty}\prod_{j=0}^{k-1}\left(1 - \frac{\int_{R^o_{(i_{1,\dots\dots} i_m)}} \lambda\left(x_c/x_o\right)dx_c}{\int_{R-R^o_{(i_{1,\dots\dots} i_m)}} \lambda\left(x_c/x_o\right)dx_c}\right) \quad (6)$$

Here R^j_{ob} is the region engaged by the earlier $'j'$ objects. Meanwhile the earlier $'j'$ objects are situated arbitrarily in R

Multi Sensor outcomes

It is necessary to detect the object through multi-sensors for various requests. Stereophonic restoration is one of the example in which the prerequisite of vision with multi-sensors can be fulfilled. Evaluation of vision possibilities by multi-sensor can be expressed as $P\left(\bigcup_{i<j}\left(E_i \cap E_j\right)\right)$ (7)

Apart from this other types of uncertainties has been taken into account like Noise, Robustness, Time varying fitness function. Generally the noise here considered from sensor output or periodical simulation's outcomes. In mathematically it can be represented as

$$F(X) = \int_{-\infty}^{\infty}\left[f(x)+z\right]p(z)dz = f(X), z \sim N(0,\sigma^2) \quad (8)$$

At this time $'X'$ is considered as design variables, $f(X)$ is time invariant fitness function, z is additive noise. It should be observed that non-Gaussian noise, such as Cauchy distributed noise has also been taken into account [13]. However, in the course of optimization, only computable fitness cost is the stochastic $f(X)+z$. Hence, the predictable fitness function in (7) is often come close to an averaged sum of a number of random trials. $\hat{F}(X) = \frac{1}{N}\sum_{i=1}^{N}\left[f(x)+z_i\right]$ (9)

Here N is sample size and $\hat{F}(X)$ is an estimate of $F(X) = f(X)$.

Robustness: The design variables are subject to variations after the optimum result has been chalked out. Thus, a communal condition is that a resolution must quiet work adequately when the design variables altered slowly (because of industrial tolerances). This resolutions are labelled as robust resolutions. To pursuit for robust resolutions, evolutionary algorithms must work on a predictable fitness function entered on the probability distribution of *P(δ)* the potential conflicts , which are regularly anticipated to be self-regulating of each other .

$$F(X) = \int_{-\infty}^{\infty} f(X+\delta)P(\delta)d\delta \quad (10)$$

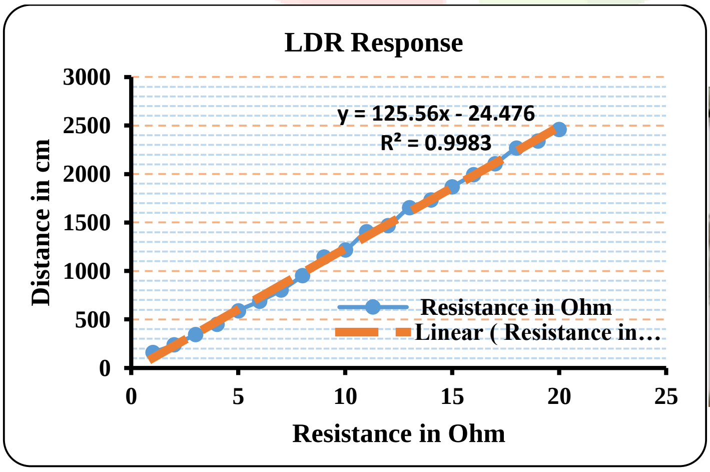
Now $F(X)$ is effective fitness function. If noise is inevitable, an individual cannot be assessed precisely.

III. EXPERIMENTS SIMULATIONS AND RESULTS DISCUSSIONS

To demonstrate the projected procedure, an experimental trials are momentarily explained here. Here a Machine vision system is well fortified with 4 dynamic sensors where each have 5 degree of freedom for proper signal detection. During the experimentation a stochastic procedure for improving the optimum sensor arrangement with respect to definite visibility necessities are targeted. To authenticate the suggested scheme, different outcomes of the procedures are presented for numerous sections, which include artificial as well as real images. A rectangular room of size 10'x12' has been taken for the proposed research.

The sensors are limited to be attached *H* = 4.5 feet directly above the base point and have a viewing angel of 90^0. A constant object mass of $\lambda = 1m^{-2}$, object height = 75cm, object radius $r = 2.5$ cm, least visibility height h=50cm and extreme visibility angle $\lambda_{\max} = 45^0$. Brighter areas signify maximum discernibility. The various sensor implemented over the MVI system is offered in Figure-2.

After implementing the sensory arrangement (both LDR and Ultra Sonic sensor) the performance of both has been studied through succeeding outcomes. Computing the error associated with the sensor during the course of illumination by lighting arrangement at different level of height or distance from the inspecting bed to the focusing point. Figure-3 and Figure-4 concludes that the LDR has approximately linear response over the illumination variation.



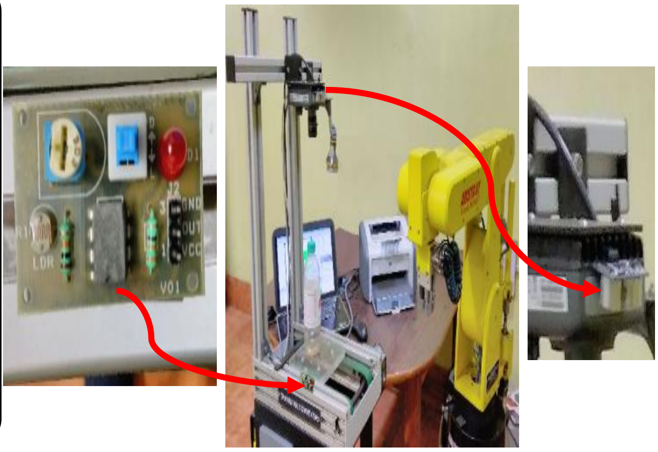


Figure-1: Sensor implemented over the Robotic MVI system

Figure-2: LDR response by considering resistance variation

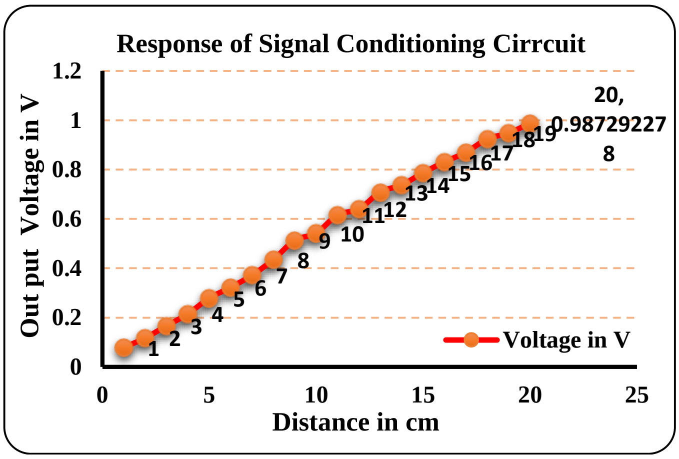


Figure-3: Signal conditioning circuit's voltage variation response

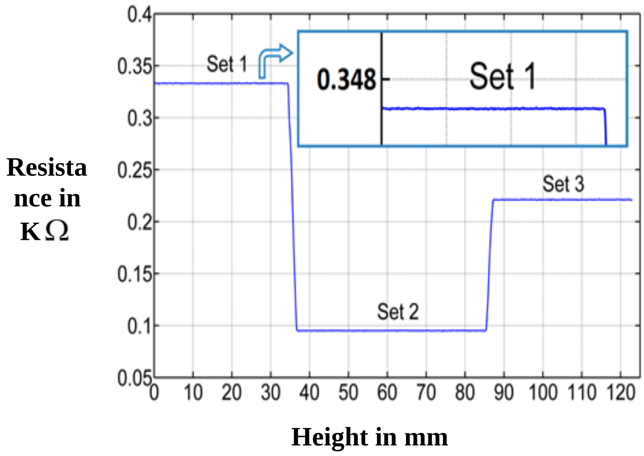


Figure-4: Determining the position of lighting arrangement for proper Illumination

Similarly Figure-5 illustrates the three different sets of proper positions out of 20 different distances or height of focusing arrangement. These values can be consider as 3 Sets of data's. In set-1, light arrangement is place almost maximum distance or height from the inspecting object, similarly in set-2 is positioned at minimum height between the object and the lighting point and in set-3 the implement is place almost middle position in between the inspecting object and illumination arrangement. The above assessment approves the proper positioning of equally sensor with the lighting arrangement in order to avoiding the dynamic uncertainty with mean absolute error of ±0.0003mm.Now the Standard deviation and variance of the lighting arrangement at different position's data presented in Figure-4 is summarized in Table-1. The demand instances are set with 2-s intervals. Vision outcomes of an individual sensor is estimated through sensor structure. Once an object is detected with pre-defined sureness, it is labeled as hurdle for its outstanding interval in the workplace.

Table-1: Discrepancy of the lighting arrangement at different positions

	Standard Deviation (mm)	Variance (mm^2)
Set-1	0.000254687	5.58851E-07
Set-2	0.000234123	4.05221E-07
Set-3	0.000254234	5.52242E-07

Table-2: Sensor Assignment visibility

Sensor	Demand Instants				
	D_1	D_2	D_3	D_4	D_5
S1	0.674	0.810	0.440	0.360	0.324
S2	0.632	0.732	0.771	0.856	0.862
S3	0.892	0.864	0.542	0.432	0.432
S4	0.792	0.779	0.432	0.002	0.943

For getting sureness in detection, a collective discernibility Matrix is cast-off. Here the K^{th} object is well-defined as $V_{SK} = \sum_j V_{SKj}$, Where V_{SKj} is the summation of the discernibility of entire sensors participating in inspection of K^{th} object at the J^{th} demand instances. The collective discernibility for all objects is presented in figure-6 and sensor tasks are shown in Table-2. From the table Sensor-2 band 3, and 4 focused on object till the recognition at demand instant 3 afterwards all assets are devoted to object-2 which effectively identified at demand instant-5.

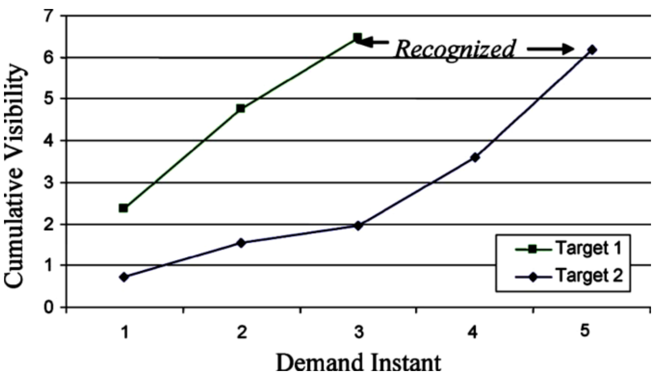


Figure-6: Cumulative visibilities for objects

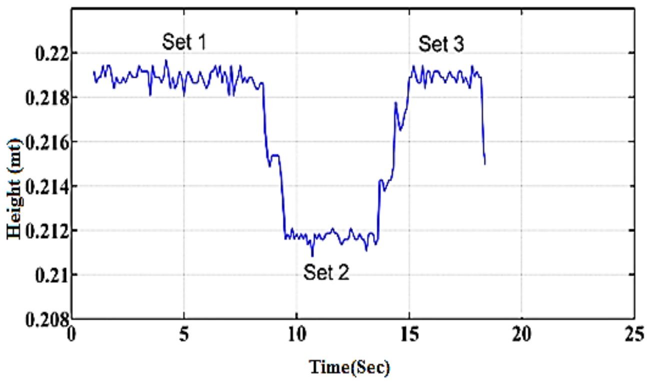


Figure-7: Sets of measuring range corresponding to static and dynamic inspecting bed

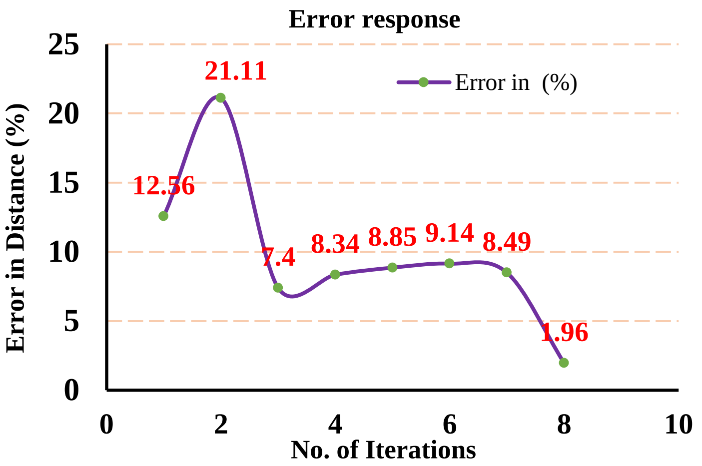


Figure-8 : Output error of US sensor in %Conclusions

Table-3: Response of an ultrasonic sensor

No. of Iterations	Real Distance (cm)	Average Obtained Distance (cm)	Error in Distance (%)
1	7.24	6.33	12.56
2	3.22	2.54	21.11
3	5.13	4.75	7.40
4	12.11	11.10	8.34
5	14.00	12.76	8.85
6	6.45	5.86	9.14
7	16.12	14.75	8.49
8	6.10	5.98	1.96

Error measurement during investigation

Sensory arrangement attached with the robotic MVI structure has some error during the inspection period because of variation in level or positioning of illumination arrangement and any obstacles present in between the inspecting object and the measuring arrangement.

To measure the error, the implement is fixed relative to the MVI structure and ensures proper illumination and considering the inspecting bed is at static and in dynamic condition for getting different values of measuring range. Figure-6 represents sets of measuring range corresponding to static and dynamic inspecting bed. Set-1 and 3 in the Figure-6 represents the illumination performance during the presence of sensory arrangement and set-2 signifies the response of the illumination arrangement with absence of sensory arrangement.

Response of an ultrasonic sensor

Implementing Ultra Sonic sensor in the Robotic MVI system and through the MATLAB simulation, the clusters of information about an object has been figured out. The Proposed structure receives the information about how far the object. In each second the system receives six sets of reading about the object.

By running the program for 50 seconds for each observation a numerous readings are obtained. There are some readings are summarized in Table-3. Figure-7 represents the output response of an ultrasonic sensor corresponding to number of iterations. As a result, the implemented sensor is capable for proper detection of positioning and distance measurement.

IV. Conclusions :

Above analysis concludes that the uncertainty dynamic environment condition due to illumination variations, object's position changes and other surrounding effects can be controlled by proper regulatory module for accurate or an error free investigation. Similarly the object position and distance measurement also possible by implementing Ultrasonic sensor. All the output obtained from these sensors has been feed to a controlling unit for proper synchronization and investigation, hence the dynamic environment conditions has to be controlled.

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