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Framework Development for Construction Safety Visualization

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Abstract: In 2011, 1,374 workers died in the United States, and many more were injured due to falls and being struck by implements. One of the major reasons for those accidents is unsafe site conditions, basically due to traditional supervision method, which is inadequate. Also, workers fail to obey safety rules and regulations due to stress caused by the progress of work, extreme environmental conditions, and their own carelessness. In order to improve upon the traditional approach to supervision, computer safety visualization can be used to monitor the construction workers. This study used image processing, image compression, pattern recognition, internet transmission, and network communication. In this study, a framework for construction safety visualization was developed. As part of this effort, an Edge Detection Algorithm was developed and tested to convert still images from the construction site into edges of the objects. The Edge Detection Algorithm was compared with other famous algorithms in terms of time-efficiency and clarity of output.

1. INTRODUCTION

A strong myth exists that accidents are inevitable during construction projects. Nowadays, this notion is fading out, and an innovative idea is emerging that zero injuries at construction sites are possible. As injuries and accidents are quite costly as well as damage worker morale, contractors have been trying to create a zero-injury culture in the construction industry. However, much effort still is necessary to avoid construction accidents.

The U. S. Bureau of Labor Statistics (BLS) website shows data for several kinds of accidents at construction sites, including falling accidents, electrical accidents, and accidents due to being struck by falling objects or flying objects or struck by equipment (BLS 2011). According to BLS, in 2011, 1,470 workers died in the United States at construction sites, and thousands of workers were injured. In the U.S., hard hats are mandatory at every construction site, and safety personnel are strict regarding their use, monitoring continuously. However, construction workers fail to obey the safety rules and regulations for many reasons, including pressure to complete work, complex schedules, and extreme weather conditions. Safety officers often find it difficult to monitor whether each and every worker is using a hard hat.

To overcome this problem, a visualization technique has been developed that can continuously monitor the construction workers and trigger a warning message if a safety rule is violated, specifically regarding wearing their hard hats. This approach can be very reliable as well as economically viable to use at construction sites because it can reduce the number of safety officers at the site and help those officers save thousands of lives.

In order to decrease the number of construction accidents, the Occupational Safety and Health Administration (OSHA) provides fall prevention training as well as other training programs to construction workers. Basically, OSHA educates construction workers in the proper use of personal protective equipment (PPE), for example hard hats, harnesses, reflecting clothing, safety shoes, goggles, face shields, filter masks, gloves, and ear plugs. The proper use of the PPE helps construction workers prevent probable accidents. With the involvement of OSHA, the fatality rate in the construction industry is decreasing; nevertheless, construction managers and safety officers still are concerned about decreasing construction fatalities to the lowest level possible.

Visualization techniques can monitor the proper use of those PPEs in real time. One visualization technique consists of installing one or more cameras at a construction site to take real-time video, which is to the office computer by means of wireless technology. Video is a sequence of still images; a computer program analyzes each image transferred from the site and issues a warning message to the appropriate personnel if hard hats are not being used.

The framework for this construction safety visualization technique consists of such devices as charge-coupled devices (CCD) to capture high-quality and uncompressed analog video at National Television System Committee (NTSC) resolution; and a hardware electronic card, which converts camera's video images into digital images as well as converts the video for transfer to the office computer. In the office computer, the compressed video is split into a number of still images, and then Edge Detection Algorithm is applied to convert the color-still images into edges of the objects or line diagrams. Once Edge Detection Algorithm is applied, a Segmentation Algorithm is applied to detect whether the line diagrams depict a worker, a hard hat, or something else. Since an image produced by a camera produces normal or non-stereo-vision, a network of cameras with proper overlap can produce stereo-vision images. The stereo-vision images can provide identity of the individual worker in the image and the distance of the worker from a fixed point; eventually stereo-vision will help to record a detail of safety rule violation history of each worker in the computer database.

Nowadays, computer vision is extensively used in several fields, for instance, construction safety, construction productivity, military, automation, transportation, and medicine. In the construction industry, it helps to make a construction site safer and more productive as well as decrease the loss of property. This research was primarily concerned with the development of an automatic detection of one or more hard hats. If any construction worker works without a hard hat, the program takes that event as a safety rule violation and dispatches an alarm with a record of that event along with the time and date of the event, recorded in the computer database. The alarm can be transmitted to cell phones or to any other devices.

2. BACKGROUND

Visualization techniques have been used in construction planning and operations. Kamat et al. (2010) demonstrated the uses of applying visualization techniques in different areas of the construction industry. Basically, they defined the scope of using visualization techniques for planning, monitoring, and controlling the techniques at two distinct levels: 1) the activity, or schedule, level; and 2) the operation, or process, level. Their research focused on visualization that could be used for both the activity level and the operation level to communicate what components were built where and when during projects.

Specifically, Kamat et al. (2010) used visualization techniques that employed dynamic operations to depict a continuously evolving, multi-storied, structural steel facility. Four-dimensional Computer-Aided Design (CAD) visualizations, which only showed the evaluation of the construction product, could be linked to project schedules. However, dynamic operation visualization could show the interactions among the various resources, including machines, materials, and temporary structures. The authors showed how this process could help the contractors build projects more efficiently and effectively.

In 2010, the Construction Industry Institute (CII) conducted a study to use pro-active real-time safety technology on equipment and workers to warn about possible accidents (CII 2010). In heavy equipment, devices were implanted that used very-high-frequency active radio frequency (RF) technology; these devices consisted of an in-cab device and a personal device. The personal protection unit (PPU) used by construction workers consisted of a chip, a battery, and an alarm. When the workers are in proximity of the heavy equipment, the alarm was set off in the equipment as well as on the workers' PPU. Field tests demonstrated that by implementing this technology, various benefits were achieved, for instance, providing real-time pro-active alerts to workers and operators and also monitoring the locations of workers, equipment, and materials. Moreover, this study included a cost-benefit analysis that showed it was economically viable to use real-time pro-active technology at construction sites.

In 2000, Curio et al. (2000) conducted a study entitled, "Walking Pedestrian Recognition." The image processing approach was used to detect, track, and recognize pedestrians crossing a road. By using two cameras, stereovision could be produced, which was useful for short-range and middle-range distances from the camera to the pedestrian. The typical characteristics of a person walking across a road were taken into consideration for recognition purposes. Specifically, the outline of the lower part of the walker — the movement of legs — was used for matching. For final recognition of a walking pedestrian, two conditions needed to be fulfilled. The first one was an outline of a human, detected by shape matching, and the next one was periodic motion of legs, also detected by matching.

Tsai et al. (2009) conducted research that studied the detection of defective traffic signals by using an image-processing model. The goal of this study was to determine whether imperfect traffic signs could be identified using computer programs. Traffic sign detection included the recognition of the type of sign and the exact location of the sign for inventory purposes. It also included identification of sign conditions, for example, retro-reflectivity; faded sign colors; tilted signs; and sign boards blocked by objects.

In the detection process, general, first the traffic sign detection is completed and then analyzing the image for traffic sign recognition is done. Tsai et al. (2009) dealt only with traffic sign detection in their study. Previously, many studies dealt with the detection of only specific types of signs, for example, speed limit signs. This research covered all types of signs, in fact, more than 670 types of signs. Traffic signs were identified in terms of their shape, color, background, and legend. A crucial step for the image processing algorithms was to separate the images that contained traffic signs from those that did not.

In 1986, Canny (2009) developed an algorithm for Edge Detection of images, using C++ programming language. Basically, this algorithm had the following five distinctive steps:

1. Smoothing: This is a blurring of an image. Every image has some amount of noise in it, and a Gaussian filter is used to smooth it.
2. Finding gradients. Edges in a grayscale image exist where the grayscale intensity changes the most; this is identified by determining the gradients.
3. Non-maximum suppression: In this step, the maxima in the gradient image are preserved, and the remaining is erased.
4. Double thresholding: The edge pixels that are stronger than higher threshold are marked as strong edges, weaker than lower threshold are suppressed, and in-between the values are marked as weak edges.
5. Edge tracking by hysteresis: Strong edges and weak edges connected with strong edges are considered to be 'certain edges'.

A research has been conducted to determine whether the person in the construction sites is a worker by the use of image processing (Oarj et al. 2012). The video frame of the construction site is analyzed to separate the moving object from background images to identify the shape of the human being. After the person is identified then by analyzing the pixel of the images, the researcher identified whether the person is a worker or not. In this experiment, the worker wore the vest and the hard hat that has a higher pixel than the person wearing the normal dress. From this pixel difference the system can determine whether the person is the worker or not.

Vision-based motion detection is used to track the construction workers unsafe working behavior (Pena Mora) by the use of video camera images (Han et al. 2012). Images from two different camera were analyzed to build the 3D skeleton model of the workers and this model was checked to figure whether the workers motion is safe or not. This research does not use the image processing method to detect the workers motion in real time.

Image processing techniques with the Kinect sensor device was used to detect worker movement at construction sites (Tharindu et al. 2012). The research's objective was to track the location of the workers at construction sites with the video camera images. The construction worker is generally identified with the images of person with hard hat. Hard hat is identified by the pattern recognition method.

Kinect sensor was sued to recognize the construction workers and their actions (Escoria et al. 2012). The algorithm used was based on machine learning techniques. The video images of the workers were analyzed to determine the accurate actions of the workers in order to assess the productivity, safety, and occupational health at indoor environments.

Many researches regarding the detection of the workers had been attempted. However the automatic construction safety violation (due to not wearing hard hat) identification system has not been developed using the image processing method.

3. FRAMEWORK DEVELOPMENT FOR HARD HAT DETECTION

A big concern to some may be to understand how the framework detects a hard hat at a construction site in real time. In other words, how does a framework, which is a computer-adapted program, identify that one or more workers are not wearing hard hats on their heads, and dispatches a message? Figure 1 shows a flowchart that describes the steps for this process.

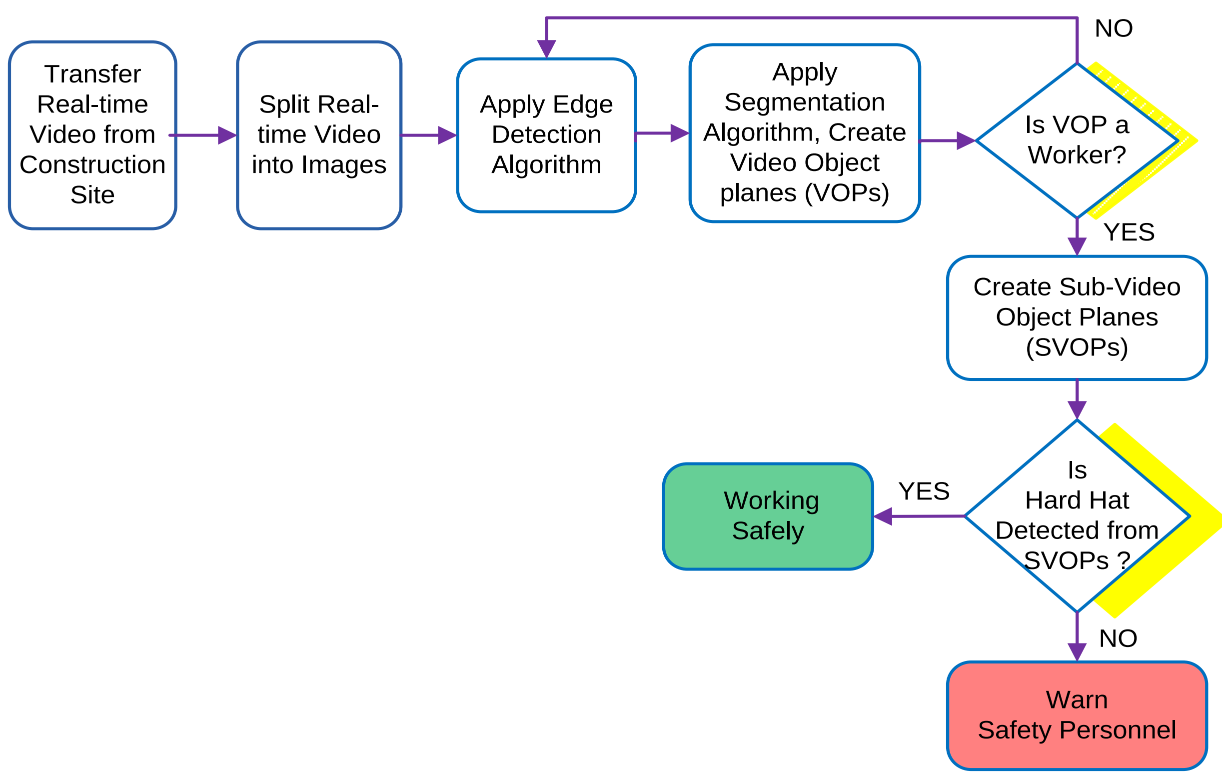

Figure1: Framework for identifying hard hats

In this research, one of the main concerns was framework development for hard hat detection, which involved real-time, automatic detection to determine whether or not people were wearing their hard hats. This was done as follows.

1. First, a camera or a set of cameras at a construction site took real-time video of workers at a site, and wirelessly transferred the images to the office computer server.
2. Because a video is a collection of images, a one-second video can be split into a certain number of frames or images. Therefore, in the second step, an Edge Detection Algorithm located in the office computer was applied to each of the frames in order to create the edges, or sets of line diagrams, of each object or worker at the site.
3. A set of line diagrams of an object is called a Video Object Plane (VOP). In the third step, the Segmentation Algorithm identifies whether or not the VOP was of a worker based on pattern recognition or shape matching of human body. If the VOP was of a worker, then the Segmentation Algorithm creates Sub-Video Object Planes (SVOPs) of the worker's VOP that is head, neck, hands, legs, etc.
4. In the fourth step, hard hat is detected from the SVOPs based on two parameters—pattern recognition or shape matching and a set of colors of the hard hats, for example red, yellow, green, and white.
5. If the algorithm program could not identify a hard hat as a SVOP after getting a VOP of a worker, it dispatched a warning message to the appropriate safety personnel.

All the algorithms are mathematical modules; the majority of the work involves developing efficient algorithms and transforming the algorithms into computer coding. In this study, only the Edge Detection Algorithm was written using C# (C-Sharp) programming. C# programming is also known as object-oriented or class-based programming.

The framework development consisted of a number of camera batteries that were powered by an arrangement of both solar and lithium batteries. Real-time video images were captured and processed by a card attached to each camera at the site. The purpose of the card was to compress the video, check for productivity, and transmit the video wirelessly to a local file server. The file server was powered by both solar panels and other power sources. One camera was connected to a file server, which applied the pattern recognition algorithm to detect each person in the camera's view. The program subsequently decided, in real-time, if each person in the view of the camera had a hard hat on or not.

If two or more cameras are used to view a person simultaneously from two different angles, and if the distance between any two cameras is known and fixed, then camera calibration can be applied prior to using the cameras for detecting whether or not people are wearing their hard hats. If an arbitrary coordinate system with its origin is assigned, then distances can be resolved of people from a specified origin of the coordinate system. Stereo-VOPs of people also can be produced.

For hard hat detection, initially, the ideal position of the hard hats on the heads of the workers was considered. Indeed, the position of the hard hat and also the position of the worker usually will not be in the ideal position for workers and their hard hats. Some probable positions and other conditions of the hard hats are identified in Figure 2. Some are rotated in horizontal while others are in the vertical. Out of six hard hats, five show the logos or initials on the front and side of the hard hats. The logos or initials give additional information to the pattern recognition system, making it easier to detect hard hats. Also, by using more than one camera calibrated at the site, the hard hats can be seen from any angle and successfully identified in stereovision.

Figure 2: Hard hats rotated in different horizontal and vertical angles

Figure 3 shows a group of construction engineers at a construction site of the Dubai Metro Project in 2008. It is clear that two of the workers were wearing their hard hats on their heads .However, the person wearing the red t-shirt was holding his hard hat in his left arm; the leftmost person also was not wearing his hard hat. Under this condition, the program would issue an immediate alarm to concerned safety personnel.

Figure 3: A construction site photo in which two have their hard hats on and two do not.

3.1 Edge Detection Algorithm

In this study, the Edge Detection Algorithm was developed and tested to convert still images into a line diagram. The metric used in to encode this algorithm was a non-Euclidian metric. The mathematical space that was operated on was a Banach space. In this Banach space, a probability metric was defined later on in the process.

Let I(x,y) be the intensity of the image at position (x,y); then, an estimate of the second partial derivative with respect to x is:

[1] $$\frac{\partial^2 I(x,y)}{\partial x^2} = \frac{I(x-1,y) - 2I(x,y) + I(x+1,y)}{2}$$

and an estimate with respect to y is:

[2] $$\frac{\partial^2 I(x,y)}{\partial y^2} = \frac{I(x,y-1) - 2I(x,y) + I(x,y+1)}{2}$$

The Laplacian, or divergence, of the gradient at the point (x,y) of the gray scale image is:

[3] $$\Delta I(x,y) = \nabla^2 I(x,y) = \frac{\partial^2 I(X,y)}{\partial x^2} + \frac{\partial^2 I(x,y)}{\partial y^2}$$

From Equations 1 and 2, an estimate of the Laplacian of the gray scale image at pixel position (x,y) is obtained:

$$[4] \quad \Delta \mathrm{I}(\mathrm{x},\mathrm{y}) = \nabla^2\ \mathrm{I}(\mathrm{x},\mathrm{y}) = \frac{\mathrm{I}(\mathrm{x}-1,\mathrm{y})+\mathrm{I}(\mathrm{x}+1,\mathrm{y})+\mathrm{I}(\mathrm{x},\mathrm{y}-1)+\mathrm{I}(\mathrm{x},\mathrm{y}+1)-4\mathrm{I}(\mathrm{x},\mathrm{y})}{2}$$

The values of the intensity all are integers ranging from 0 to 255. Multiplication by 4 can be obtained by shifting the integer two times to the left. Division by 2 is obtained by first adding 1 to the numerator if the numerator is positive or by subtracting 1 from the numerator if negative, and then shifting the numerator to the right by one. The estimated Laplacian for any image could be negative or positive, with the majority of the values being equal to zero and is symmetric about zero. The probability density function of the Laplacian is:

$$[5] \quad \mathrm{f}(\mathrm{x}) = \frac{1}{\sqrt{2}\sigma} \mathrm{e}^{-\frac{\sqrt{2}|\mathrm{x}|}{\sigma}} \qquad -\infty < x < \infty$$

The standard deviation 'σ' depends on the quality of the camera, the light intensity of the scene, and the number of edges as well as the type of edges. For example, edges both of metallic objects and steel objects reflect light differently than edges of non-steel material. The edges of an image represent a relatively small percentage of the pixels of the image; those points are part of the tails of the probability density function of Equation 5. Development of the Edge Detection Algorithm consisted of finding the edges and it using the following steps.

1. Compute the Luma component of the image,
2. For every Luma component pixel, compute the second-order partial derivative with respect to x, using Equation 1,
3. For every Luma component pixel, compute the second-order partial derivative with respect to y, using Equation 2,
4. For every Luma component pixel, compute the Laplacian at position (x,y), using Equation 3,
5. Compute the histogram of the values obtained in Equation 4,
6. All the values for which the area of the histogram to the right is less than 2.5% are edges,
7. All the values for which the area of the histogram to the right is less than 10% are possible edges,
8. If any of the neighbors of a possible edge is an edge, then the possible edge is an edge.

4. APPLICATIONS OF EDGE DETECTION ALGORITHM

For hard hat detection in an image, several steps need to be executed. Among those steps, image processing is the area of focus in this study. Different algorithms take different processing times; therefore, an efficient algorithm is very important for the actual execution of a program. Furthermore, there are several other factors that play a role in making a program efficient, for example, image compression. For this study, time-efficient algorithms were needed.

The Edge Detection Algorithm used in this study involves eight steps to detect edges of objects of an image (Shrestha et al. 2011). In the first step, the luma component of every pixel—that is, the intensity values of the pixels—are determined. In the second and third steps, the second-order partial derivatives of the luma components are determined with respect to x and y. After this, the Laplacian for evey luma component is computed. In the sixth step, a histogram is plotted for all the values calculated from step 4.

Basically, the histogram is normally distributed, and the pixels that are 2.5% to the right or tail are considered to be edges. Moreover, all the values that fall under 10% to the right of the histogram are probable edges. The probable edges will be edges if their neighbors are edges; otherwise, false. Because the steps are simple and there are not any complex loops in the coding, this algorithm seems to be much faster in comparison to other algorithms. One famous Edge Detection Algorithm, that of Dr. John Canny, shows clear edges and a low signal-to-noise ratio; nevertheless, it takes more time to process the images in comparison to the algorithm developed and used in this study (Maini and Aggarwal 2009).

The Edge Detection Algorithm is the first step of the framework development for construction safety visualization. It converts the objects of construction sites that are in still images into line diagrams, or edges, of the objects. As an example, a photo taken of a hard hat with the University of Nevada, Las Vegas (UNLV) logo (Figure 4) shows the upper semicircle, the base, and the logo both in the RGB photo and line diagram. The color images created from video are converted into the gray-scale images prior to using Edge Detection Algorithm in order to reduce the file size of the images.

Preliminary results show that the hard hats which have safety stripes in the back and logos are easier to recognize because they provide additional information to the pattern recognition system. Camera systems are relatively inexpensive; they could be self-powered and are easy to install. They could be connected on site and from there, transmit wirelessly to offsite computers. Thus, they can automatically monitor if everybody is wearing their hard hats and other Personal Protective Equipment (PPE). In the case where there is a violation, the computer can issue a violation alarm or any other kind of information, making the supervisors aware of the violation so that they can take corrective action prior to accidents occurring.

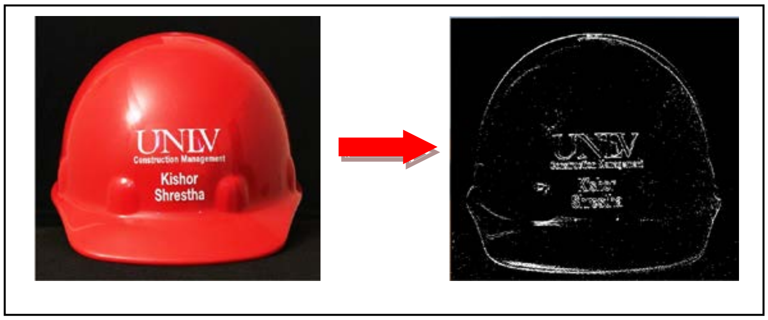

Figure 4: An RGB photo of a hard hat (left) and its line diagram after image processing with an Edge Detection Algorithm

Similarly, the left-hand RGB color photo, shown in Figure 5, was converted into a grayscale photo, as shown in middle photo of Figure 5. As shown on the right side of Figure 5, the VOP of the author was obtained by applying the Edge Detection Algorithm on the middle image of Figure. Therefore this image contains both VOP detection for a person and a SVOP detection of the hard hat.

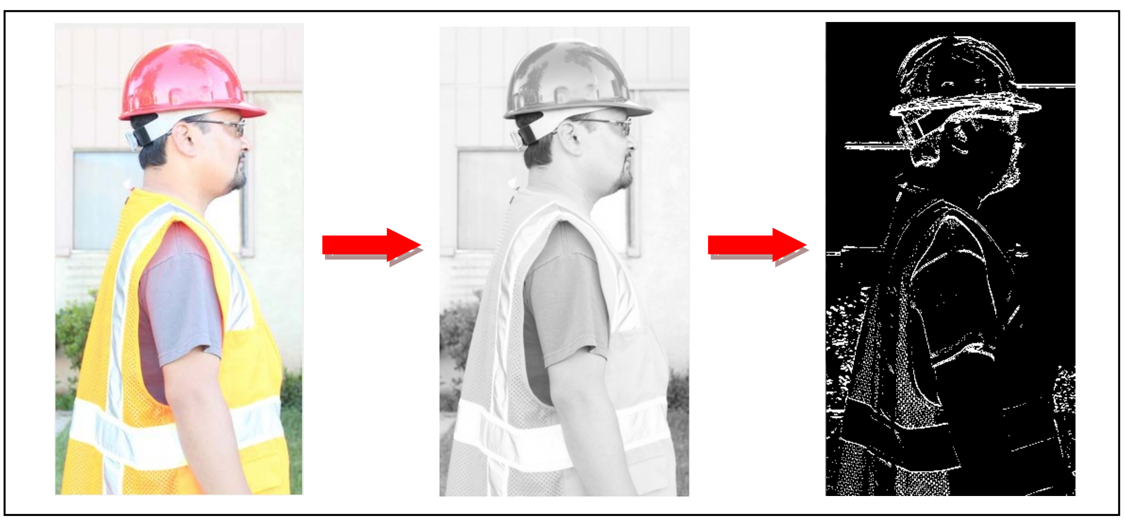

Figure 5: An RGB photo of an author with a hard hat (left), its grayscale image (middle), and line diagram with the VOP of a person and SVOP of a hard hat

The two characteristic semicircles of the hard hat can be seen, the upper semicircle whose chord forms an angle with the x-axis and the slightly deformed horizontal semicircle. The relative clarity of the safety jacket — as well as the clear definition of the ear, mouth, nose, eye, arm, and hand — all can be noticed in the picture. All of these are part of the features included in the computerized hard-hat recognition algorithm.

Figure 6 (left) is a photo of two workers, one wearing his hard hat and the other not. First, the Edge Detection Algorithm was applied, and a line diagram generated (Figure 6, right). Next, the VOP separated each person in the camera view. Finally, the Segmentation Algorithm detected no hard hat for the person on the left. Comparing the geometrics of a hard hat with a no-hard-hat head, notice the upper semicircle of the man's head is similar to that of a hard hat, but differs from the hard hat semicircle in that 1) it is larger than a semicircle; 2) it is not as smooth as a hard hat semicircle; 3) it does not provide discontinuity with the rest of the head and neck, which a hard hat does; and 4) it does not have the lower profile of a hard hat. By comparing the two images, the program recognizes an SVOP hard hat.

Figure 6: An RGB photo of two workers (left) one with no hard hat and the other with a hard hat. The program can distinguish the VOP of each worker as being with and without a hard hat.

Since this is the first step of the Framework development for construction safety visualization study, the edge detection algorithm was developed and it has limitation of effectiveness and efficiency. A couple of construction site images were tested and resulted that the program is not effective at the following adverse conditions.

1. The background and object do not have sufficient contrast to distinguish edges of hard hats,
2. The working area is dark or light is not sufficient to detect hard hats,
3. The color of the hard hat is exactly or very comparable to the background color.

Along with ineffectiveness at above conditions, this edge detection program takes 3.75 seconds, 1.90 seconds, and 1.50 seconds for 216 x 325, 130 x 390, and 160 x 266 pixel images respectively to convert into a line diagram images which is comparatively slower than required speed to be used for real-time video. Therefore the program will be improved on effectiveness and efficiency in further study.

5. CONCLUSION

A framework for construction safety visualization was developed and a program file for coding of the edge detection algorithm was developed in this research. The edge detection program takes 3.75 seconds, 1.90 seconds, and 1.50 seconds to analyze 216 x 325, 130 x 390, and 160 x 266 pixel images respectively. To analyze the images in real-time, a program could be able to analyze at the rate of 16 to 30 images per second. Therefore this program requires improving the efficiency of analyzing the images at a minimum of 16 images per second to be used for real-time construction safety visualization. Moreover, for further effectiveness of the program, it requires to improve the algorithm in order to detect worker and hard hat at most of the construction site condition in an accurate way.

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