Recognition of LED Characters on a Handgrip Dynamometer Using Connected Component Labelling and K-Nearest Neighbor

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Abstract

Handgrip Dynamometer is a measuring device that is often used in the health sector to determine the level of strength or hand grip resistance. This tool has two main components, which are a handheld stick that is used as a handheld media and a screen in the form of an LED panel to display results of information or the value of the grip strength. However, this tool generally is not able to be integrated by computers or other storage devices. Also, the test results cannot be stored or used in collecting data on a large scale. Based on this problem, the research is intended to perform automatic character recognition on the LED screen so that the displayed value can be computerized. The tool used in this design is MIE Pinch or the Grip Digital Analyzer. In short, the LED panel image is taken ten times for each test (one frame per second) using the camera, where this image will be used as the input image. Then the pre-processing process is carried out to fill the gaps between segments in the characters using morphological operations to become one intact area. After that, the Connected Component Labeling (CCL) process is carried out to segment each number on the panel. Finally, the K-Nearest Neighbor (KNN) method is used to introduce each character using classification techniques with previously trained image data. The test results show that the accuracy rate of LED recognition in the tested scenario has a success rate percentage of 84.48% based on 290 valid images from 300 images taken.

Keywords: LED; connected component labeling; k-nearest neighbor; handgrip dynamometer.

1. Introduction

Grip strength is one of the most important aspects in determining the success of the hand treatment and rehabilitation strategy. The strength mentioned is the maximum ability that a person can do to grasp under normal conditions (Oseloka, 2014). Research on grip strength has also been studied to predict health, liver disorders (Silventoinen, 2009), cerebrovascular disease, disability, decreased cognitive abilities, risk of fractures, and a person’s death (Cooper, 2014). In addition, other studies link the correlation between grip strength and other components in the human body such as nutrient and nutrient content, bone content, and muscle strength (Liao, 2016). Many researchers on grip strength also conclude that there is a strong correlation or relationship between grip strength and various other factors such as age, hand length, body mass index (BMI), and even the circumference of the upper arm (Martin, 2015). This causes the use of medical devices to measure the level of a person’s grip strength is needed so that it can always be further examined.

One tool that is often used to measure the level of strength of a person’s grip is a handgrip dynamometer. This tool will display the value of a person’s grip strength in kilograms or newtons (depending on the specifications and tool options) on a screen or panel which is generally light emitting diodes (LED) technology when the grip tool is held. Some literature regarding studies to process the values obtained have also been carried out, such as research to determine the grip strength in children and adolescents (Tapan, 2017), as well as studies to find out the difference between grip strength in dominant and non-dominant hands (Koley, 2009). Meanwhile, several other studies conducted tests to recapitulate and record grip strength in healthy adults, where the greatest grip strength is in populations in continental Europe and North America (Leong, 2016). In Indonesia, research on hand grip strength can be said to be very minimal because there is no reference data that can be used and the limitations of the data collection process. In fact, based on the studies discussed earlier, it can be concluded that to process and examine data at further level, large-scale testing and the ability of measuring instruments to store test results are required. However, many handgrip dynamometer tools in circulation do not have storage media or other technology to keep track of the test results. This becomes a major obstacle that data on handheld strength for the population in Indonesia is difficult to collect and obtain, causing medical research on handheld strength to be less in demand.

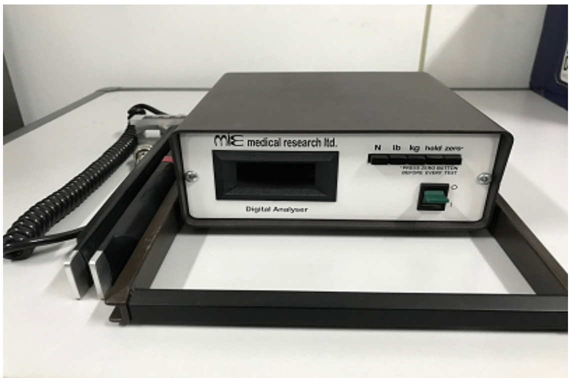

Fig. 1. MIE Digital Grip Analyser

Based on these limitations, this study is aimed at designing a system for recognizing LED characters on a dynamometer handgrip measuring instrument. This is demanded so that the test results can be stored in a computerized manner, with the aim of simplifying the process of retrieving and storing data. The tool used in this study is the MIE Pinch / Grip Analyzer, which this tool has two main components, such as the grip stick and the LED panel to display the test results. The output on this LED panel will be captured and processed using image processing techniques so that the displayed value can be recognized and stored. It is then hoped that through this research, further research can be developed on the strength of the handheld using the data that has been collected.

2. Research Method

The proposed method consists of two main parts, which are the detection and recognition stages. At the detection stage, the LED panel area is first obtained. Then, the LED characters will be segmented so that an image for each numeric character will be obtained which is displayed on the dynamometer handgrip. Finally, the recognition of each number in the image is carried out using K-Nearest Neighbor (KNN). A description of these processes can be seen in the details below.

2.1. Image Capture and Cropping

Before the retrieval process, the subject will be demonstrated how to use a dynamometer handgrip, which is how to grip and the grip duration needed. In this test, the image is taken every second for ten seconds, so the subject is required to hold the hand grip tool for ten seconds. That way you will get ten images for every test. The image of the LED panel was taken using a camera (webcam) with a resolution of 1280 x 720 pixels, with a camera and LED panel distance of about 15 cm. After the image is obtained, cropping is done automatically to get the LED panel area. This is done so that other components that do not need to be recognized do not become noise or interfere with the next process. Each LED panel image will be processed individually at the next stages.

Fig. 2. LED Panel Area Taken

2.2. Pre-processing

After the image is obtained, then the pre-processing stage is carried out on the image. This stage is a crucial stage before the image enters the next process stage. In the LED character, the representation of a number is displayed using a 7-segment concept. This causes each digit or character on the LED panel to have separate segments and are not connected to each other. At this stage, the LED character digits are linked into one part so that it can be processed at the segmentation stage using Connected Component Labeling later on. The initial step at this stage is grayscaling and thresholding to separate the object (in this case the LED number) and the image background.

To connect the segregated areas into one intact area, one morphological operation, closing, is carried out. Closing is a dilation process followed by erosion, the resulting effect is filling small holes in objects, combining near positioned objects, and generally smoothing the boundaries of large objects without changing the object area significantly (Bishnoi, 2014). Closing is useful for smoothing the image and removing small holes. So that in practice, the closing process is used on the LED display to connect the closest segments of each character and become one unit. The closing operation consists of a dilation operation followed by erosion, so the equation can be defined as follows (Raid, 2014):

$$g(x,y) = (f(x,y) \oplus SE)\ \theta\ SE \tag{1}$$

2.3. Connected Component Labelling

The results of the pre-processing image are then segmented using Connected Component Labeling (CCL). Connected Component Labeling is a process of identifying pixel components that are connected to each other in an image by marking each pixel as a unique label stored on a matrix (Rajaraman, 2013), as seen in Fig. 3. With this method, segmentation will be carried out to separate each character number on the image. The label operation of the object area assigns a unique name or number to all pixels of 1 contained in the area. The labeling result is the individual extractable component. The Connected Component Labeling algorithm can work on binary images using the 4-connectivity or 8-connectivity method. In the 4-connectivity method, the neighbor check is done on the top, bottom, left and right pixels. Meanwhile, on 8-connectivity, the neighbor check is done to all neighboring pixels.

0	1	1	0	2	2	2	0
0	1	1	0	2	2	2	0
0	1	1	0	2	2	2	0
0	0	0	0	0	0	0	0
0	0	0	0	3	3	3	0
0	0	0	0	3	3	3	0
0	0	0	0	3	3	3	0

Fig. 3. Linked Pixel Label

The labeling process is carried out by using a marker which functions to find the point *p* which indicates the pixel where the label will be located and assigned to the foreground area. When the condition is true, it will be checked to all neighboring points from *p* (depending on the number of n-connectivity). If all neighbors are the background area, then a new label will be assigned to p. But if only one neighbor is foreground, label *p* is the same as neighbor label. That way, every character will be given a different label so that one character from another can be separated based on the label it has.

2.4. K-Nearest Neighbor

The K-Nearest Neighbor (KNN) algorithm is a method for classifying objects based on learning data that is closest to the object (Liantoni, 2015). The KNN algorithm is a method that uses a supervised algorithm. The difference between supervised learning and unsupervised learning is that supervised learning aims to find new patterns in data by connecting existing data patterns with new data. Whereas in unsupervised learning, the data does not yet have any patterns, and the aim of unsupervised learning is to find patterns in data. So that the results of the newly classified test sample are based on many of the categories on the KNN.

The purpose of the KNN algorithm is to classify new objects based on attributes and training data (Tapan, 2017). In its application, the KNN algorithm is a simple algorithm, which is by using the neighbor classification as the predictive value of the new sample test data using distance calculations. Learning data is represented as a multi-dimensional space, where each dimension stores features or values from the trained data (Ong, 2016). In this study, the training data used were binary images in the form of numbers from 0 to 9. Meanwhile, the distance calculation used was the Euclidean Distance. In general, the KNN algorithm can be described as follows (Liantoni, 2015):

1. Determine parameter *k*, which is the number of closest neighbors.
2. Calculate the distance of the new image data (segmentation results) with all training data using the Euclidean Distance.
3. Sort the distance and determine the closest neighbors based on the minimum *k*.
4. Determine the closest neighbor category.
5. Use the simple majority category from the closest neighbor category as the new predictive value.

3. Results and Discussion

Experiments are carried out using a dataset in the form of 79 numeric images from numbers 0 to 9, where each number represents each class that will be used in the KNN process. Image size of 87x131 pixels obtained through the segmentation process. In the experimental stage, each image is taken using the camera every second for 10 seconds, so that 10 test images are obtained which are used as input to the system. The number of tests performed was 30 times, so that the total number of recognized images was 300 images. However, image capture does not always provide an appropriate numerical representation because the value on the measuring instrument changes continuously due to motion blur effects. So that during evaluation, the test image will be checked first whether the value displayed on the LED panel is valid or not. Unsuitable images will be considered invalid images and will not be considered when evaluating the system and calculating accuracy. The sample of an invalid image is shown in Fig. 4. Based on the scenario above, the system performance can be seen in Table 1. The average accuracy value of the proposed system reached 84.48% with an average recognition time of about 1.49 seconds.

Fig. 4. Sample of an Invalid Image

Table 1. The test results using k-nearest neighbor

Category	*Valid Image*	*Correct Recognition of Valid Images*	*Accuracy*	*Average processing time (seconds)*
1	10/10	10/10	100%	1.7515
2	10/10	6/10	60%	1.5451
3	10/10	8/10	80%	1.4876
4	9/10	5/9	55.56%	1.4296
5	10/10	10/10	100%	1.4546
6	10/10	10/10	100%	1.4998
7	10/10	8/10	80%	1.5579
8	10/10	10/10	100%	1.5016
9	9/10	8/9	88.89%	1.5501
10	10/10	7/10	70%	1.4563
11	9/10	7/9	77.78%	1.4515
12	10/10	10/10	100%	1.4436
13	9/10	6/9	66.67%	1.4452
14	10/10	10/10	100%	1.4500
15	10/10	10/10	100%	1.5281
16	9/10	8/9	88.89%	1.4124
17	8/10	5/8	62.50%	1.6421
18	9/10	8/9	88.89%	1.4452
19	10/10	8/10	80%	1.4374
20	10/10	10/10	100%	1.4514
21	10/10	8/10	80%	1.4311
22	10/10	9/10	90%	1.5421
23	10/10	5/10	50%	1.4374
24	9/10	8/9	88.89%	1.4655
25	10/10	9/10	90%	1.6155
26	10/10	8/10	80%	1.5607
27	10/10	9/10	90%	1.5184
28	10/10	9/10	90%	1.4139
29	10/10	7/10	70%	1.5155
30	9/10	9/9	100%	1.5328
Average	290/300	245/290	84.48%	1.4991

4. **Conclusions**

In this study, the implementation of the CCL and KNN methods to detect and recognize characters in the form of numbers on the LED panel has been successfully carried out. In the test evaluation, not all input images can represent the appropriate numbers because when taking images using the camera, there is a possibility that the numbers on the panel are still in the transition process of changing numbers so that the captured image does not display a clear number. Of the 300 images tested, 290 valid images with the percentage of successful recognition reached 84.48%. Meanwhile, the average time needed by the system to process an image is 1.49 seconds. This is because the time used is mostly to calculate the distance between the tested image and each training image.

However, the proposed method still has some limitations such as a static camera position (not shifted far) and some LED numbers cannot be recognized properly because of the over-segmentation method in the CCL segmentation process. This causes other areas that are not numerical representations are also recognized by system and cause an introduction error. This can occur mainly because the lighting is too bright while the shooting happens, which then some parts that should be the background of the image become noise due to the reflection of the objects. Suggestions for further research are to use a method to find the LED panel area or detect numbers automatically using certain algorithms such as the Run-Length Smearing Algorithm (RLSA) or OCR to detect characters or text in the image.

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