A COMPARISON BETWEEN TWO IMAGE DETECTION ALGORITHMS ON NECK ANGLE DETECTION AND A PROLONGED USAGE CLASSIFICATION CONCEPT

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ABSTRACT Regarding the text neck syndrome, in our previous work we proposed a solution to accurately detect a neck angle while using a smartphone. In this paper, to improve the accuracy and calculation speed, we performed a comparison between two image processing algorithms, which involved in calculating neck angles while using the smartphone. The two image detection algorithms were Haar and LBP (Local Binary Patterns). Both of them had their own advantages and disadvantages. The main difference between the two algorithms was that Haar used floating-point for the calculation, while LBP used integer numbers. The comparison showed the differences of the two algorithms in terms of accuracy and calculation speed. Both Haar and LBP classifiers were trained with 900 positive images and 2,842 negative images. This experiment showed that a combination of both Haar and LBP algorithm had benefits for our system the most. Moreover, for a more effective neck angle detection system, we also proposed a classification of unhealthy neck angle which also concerned with the duration of smartphone usage. This work would encourage the user to have a more healthy neck angle while using the smartphone

1. INTRODUCTION

The growth of smartphone has been significantly increased in recent years. Based on the Smartphone Ownership Update in 2013 (Smith, 2013), the report had shown that at least 56% of American adults were smartphone owners and that the percentage of smartphone owners would continue to increase as the percentage of other kinds of cell phone owners decreased and faded away eventually. However, the increment of smartphones also came with consequences.

Nowadays, many syndromes have occurred due to the

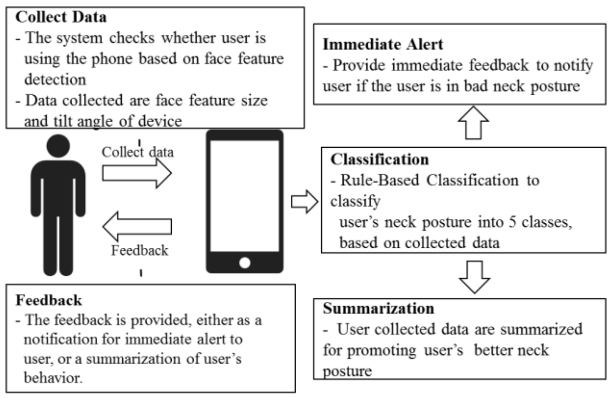

Fig. 1 Overview of Smartphone Monitoring System to Prevent Unhealthy Neck Posture

unhealthy usage of technologies. As the popularity of smartphone usage has grown dramatically in the recent years, the bad consequences have also come with it. Many syndromes have been pointed out as the consequences of using smartphone. For computer vision syndrome (CVS), it was showed that two of the causes for CVS were poor work station setup and inappropriate glasses for computer uses (Yan et al., 2008). This showed that the CVS could be avoided by using an appropriate approach. For a text neck syndrome, our previous study had proposed the solution to prevent an unhealthy neck posture which led to the text neck syndrome (Lawanont et al., 2015). An overview of our system is shown in figure 1.

Many other works have also proposed methods to prevent different kinds of syndromes. These works make use of the advance of technologies such as sensors in smartphones and image processing techniques.

In this paper, we discuss the image processing algorithms and techniques used in our previous work for determining the neck angles of the users. Our work shows the performance evaluation of the two algorithms in the experiment section. In addition, this paper proposes the concept of implementing a neck angle classification rule for a prolonged usage of smartphones.

2. METHODOLOGY

In this section, we discuss the methods used in this paper; first, the method used for testing the performance of image detection algorithms, and second, the classification concept which considers a prolong usage of smartphones.

2.1 Image Detection

2.1.1 Haar and LBP

Haar and LBP (Local Binary Patterns) are two famous algorithms for image detection. In our experiment, these two algorithms were tested under the same setting, same resources of computer and smartphone, and on the same set of images.

Haar cascade classifier was proposed by P. Viola (Viola, 2001) and M. Jones in 2001. Its concept was to use the image features instead of using the pixels directly, one of the good reasons to use the features instead of the pixels was that the feature based system could perform much better than pixel in terms of calculation speed. Haar cascade used floating point numbers in calculation to detect the features.

LBP (Local Binary Patterns) was another type of texture analysis. In LBP, the method approached the texture analysis by using the so-called texture unit. LBP used a gray scale method like Haar. However, LBP used integer numbers in order to compute the texture unit.

2.1.2 Classifier Training

In training for Haar and LBP classifiers, we used a set of 3,742 images. The training set was from human samples, INRIA databases (Everingham et al., 2014) and VOC2012 (Gourier et al., 2004). The training set included 900 positive images and 2,842 negative images, where positive images were images which contained the object of interest, e.g., mouth, eyes, or face. While the negative images were any images that did not contain any object of interest. The classifier training was done on an offline computer.

Each classifier training parameters for both LBP and Haar was set as follows, stage parameter was set to 20 with minimum hit rate of 0.999 and maximum false alarm rate of 0.5.

2.2 Prolong Usage Classification

Our previous work, based on a medical research (Hansraj, 2014), had shown that it was significant to detect neck angles while using smartphone, as this could lead to a text neck syndrome. Figure 2 shows the five neck positions and weight felt by the spine in each position. However, the duration of the phone usage should be considered as well.

Position	Neutral	15°	30°	45°	60°	90°
Force to Cervical Spine	10-12 lbs.	27lbs.	40lbs.	49lbs.	60lbs.	Not Measurable

Fig. 2 Five Neck Positions (Hansraj, 2014)

Table 1 Classification Rules Based on Duration of Smartphone Usage and User's Neck Angle

Duration (Minutes) / Neck Angle (Degree)	0-7.5	7.5-15	15-22.5	22.5-30	>30
0-15	A	B	C	D	E
15-30	B	C	D	E	E
30-45	C	D	E	E	E
45-60	D	E	E	E	E
>60	E	E	E	E	E

One article had shown that there were several causes for the neck pain and one of them was the prolong usage (Walsh, 2015). It suggested that in order to prevent such kind of pain, several methods could be used. The article pointed out that standing up and moving every 30 minutes would be useful to prevent either an office syndrome or the neck pain.

By applying this rule to the classification, the classification should not classify based on only the user's neck angles, but to classify the user based on his/her duration of usage as well. Table 1 shows the classification rules which are the combination of the prolonged usage and the neck angle. The neck angle is classified based on the medical research which reflects the weight felt by the spine. The usage duration is divided into 5 periods, with the maximum of 30 minutes, to match the 5 classification rules. Class A is Very Healthy; B is Healthy; C is Slightly Unhealthy; D is Unhealthy, and E is Very Unhealthy. The combination of the two factors is done by the following methods:

- Smartphone usage duration is less than 7.5 minutes; the classification is done purely based on the neck angle.
- Smartphone usage duration is between 7.5 – 15 minutes; this will be classified to the class which is one step higher than the actual neck angle class.
- Smartphone usage duration is between 15 – 22.5 minutes; this will be classified to the class which is two steps higher than the actual neck angle class.
- Smartphone usage duration is between 22.5 – 30 minutes; this will be classified to the class which is three steps higher than the actual neck angle class.
- Smartphone usage duration is longer than 30 minutes; this will be classified as very unhealthy for all neck angles.

3. EXPERIMENT

In this section, we described the experiment conducted to test and compare the performance of two image detection algorithms, Haar and LBP, and the results are shown and discussed.

3.1 Overview

We considered that this experiment would be meaningful to our previous work only if the experiment was done on the smartphone, which was the platform for our system. Thus, the Android application was developed on Android 5.1.1. The device used to test the algorithms was Samsung Galaxy S6 Edge.

The application made use of the OpenCV library to run the image detection algorithms. First, either Haar cascade classifier or LBP cascade classifier was loaded. Then, the image was loaded, and the detection process started. Last, the new image was saved to the storage with detection squares drawn on the picture. The loop iterated until all the images were loaded. A total of 500 images were used to test each classifier, and the calculation time was recorded along with the results of the classification. Figure 3 shows the example images saved to device after they have been loaded into the detection process. The results of Haar classifier are on top and LBP are at the bottom, with a), b), and c) are the images from face, eyes, and mouth classifiers, respectively.

Fig. 3 Example of Image Results after Detection Process

3.2 Experiment Results

Table 2 shows the results of the experiment conducted through the application we developed. Please note that ‘Hit’ means the classifier correctly detects the object in the picture; ‘Miss’ means that it fails to detect the object, and ‘Fault’ means false alarm or that it has detected another object which is not the object of interest. There were a total of 500 objects of interest in each image set for testing the classifiers.

The same type of classifier was tested on the same set of image. For example, face classifiers, for both Haar and LBP algorithm, were tested on the same set of images, and the same practice was applied to mouth and eye classifiers as well. A perfect result would be 500 hits, 0 miss, and 0 fault.

Table 2 Result of Image Detection Algorithm Performance Testing

Classifier	Algorithm Type	Time (seconds)	Hit	Miss	Fault
Face	Haar	578.02	487	13	79
Face	LBP	155.99	429	71	77
Mouth	Haar	284.11	490	10	25
Mouth	LBP	143.20	486	14	75
Eye	Haar	211.78	457	43	57
Eye	LBP	145.67	343	157	45

For face classifier with Haar algorithm, it completed the test with a total time of 578.02 seconds, with 487 hits, 13 misses, and 79 faults. While face classifier with LBP algorithm completed the test with 155.99 seconds with 429 hits, 71 misses, and 77 faults.

For mouth classifier with Haar algorithm, the test took 284.11 seconds with 490 hits, 10 misses, and 25 faults. On the other hand, mouth classifier with LBP algorithm completed the test in 143.20 seconds with 486 hits, 14 misses, and 75 faults.

For eye classifier with Haar algorithm, it took 211.78 seconds to complete the test with 457 hits, 43 misses, and 57 faults. While the LBP algorithm took 145.67 seconds with 343 hits, 157 misses, and 45 faults.

From the results, it showed that in each classifier, LBP had significantly outperformed Haar algorithm in terms of time used to detect the objects, especially in face classifier where LBP was almost 4 times faster than the Haar algorithm. Eye classifiers showed the least difference in time used. However, in terms of accuracy, Haar had outperformed LBP algorithm in every classifier, with the most noticeable result in the eye classifier where Haar had made a total of 457 hits (91.4%), while LBP only achieved 343 hits (68.6%). Overall, all Haar classifiers had managed to maintain the accuracy above 91% while LBP failed short to do that in the eye classifier.

Even if the results might show that Haar took more time to detect the objects of interest, but bear in mind that the best solution should be chosen. For the face classifier and eye classifier, it would be more suitable to use the Haar algorithm even if the detection time was higher than LBP, but the lack of accuracy of LBP should not be tolerated. While for the mouth classifier, using LBP classifier would be a better solution, as the accuracy was very similar between Haar and LBP (98% and 97.2%, respectively). Even the faults of LBP were higher than Haar, but in the real world situation, we could reduce the chance of having false alarms by narrowing down the area to be loaded into detection process. For example, after the face was detected, we could divide the face into two halves, the top half and the bottom half. The top half could be loaded into the eye classification process, while the bottom half could be loaded into the mouth classification process. By doing this, the area where the classification needed to look for the objects was narrowed down. Thus, there would be fewer chances for false alarms.

4. CONCLUSION

From this work, we have showed the results of our experiment on the two image detection algorithms, Haar and Local Binary Patterns (LBP). The results showed that the combination between Haar and LBP should be used. We decided that for the best of our previous work, face and mouth should be detected by using Haar algorithm, and eye should be detected by using LBP algorithm.

As for a future work, the results had given us a guidance to develop a more complete system with better performance.

On another perspective, currently all the processes, such as loading image, detecting object, and classification are done locally on the Android smartphone. A cloud-enabled process could be brought in to reduce the smartphone processing workload. However, to use the cloud process, the device must be connected to the Internet all the time, and the data usage charge may be applied. This issue must not be overlooked for the matter.

Overall, we believe that this work would encourage the smartphone users to have a better health based on their usage. The full system would help them realize their behaviors and eventually lead them toward a healthier usage.

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