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Tracking Hand Trajectory as a preliminary study for Hand Hygiene stages

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Abstract

The process of hand washing involves complex hand movements. There are six principal sequential steps for washing hands as per the World Health Organisation (WHO) guidelines. In this work, a preliminary analysis was undertaken in order to develop an automated image processing system for tracking and classification of two-handed dynamic gestures involved in hand washing. To facilitate this study, videos of healthcare workers who were engaged in washing hands were sourced from the internet. The videos were analysed in order to extract the unique features of two-handed gestures associated with all hand hygiene (HH) stages. The combination of these unique features can be used to detect each HH stage. In the video recordings, the hand trajectory was found to be linear or circular for all six HH stages. In this paper, we attempt to track hand trajectory with the help of 2.5 Mega Pixel ELP-USB cameras and using an image processing approach for skin detection and the contour-centroid detection method. The YCbCr colour space is invariant to illumination intensity and therefore it was selected for the skin detection method. This work concludes that cameras are suitable for tracking one hand movement- linear and circular motion as a preliminary work and can be further expanded for detecting two hand movements in hand washing.

Keywords: Image Processing, Hand Hygiene, 3D sensors, Gesture Tracking and Recognition

1 Introduction

According to the European Centre for Disease Prevention and Control (ECDC), 2.5 million cases of Hospital Acquired Infections occur in European Union and European Economic Area (EU/EAA) each year, corresponding to 2.5 million DALYs (Disability Adjusted Life Year) which is a measure of the number of years lost due to ill health, disability or an early death [1]. MRSA-Methicillin Resistant Staphylococcus Aureus is a common bacteria associated with the spread of Hospital Acquired Infections (HAIs) [2].

One method to prevent the cross transmission of these microorganisms and to reduce the spread of HAIs is the implementation of well-structured Hand Hygiene (HH) practices. The World Health Organization (WHO) has provided guidelines about hand washing procedures for health care workers [3]. Best HH practices have proven to reduce the rate of MRSA infection in a health care setting [4].

One challenge in a dynamic healthcare environment is to ensure compliance with these HH guidelines and to evaluate the quality of hand washing. This is often done through audits involving human observation. The hand washing process, however, is well structured and has particular dynamic hand gestures associated with each hand washing stage. The assessment of the process may therefore be suited to automation.

Existing technology for monitoring hygiene activity includes the use of electronic counters and RFID badges to measure the soap usage and location based reminder systems to alert the workers about washing hands [5, 6, 7].These systems have shown to improve the frequency of hand washing but they do not assess whether the process of handwashing is compliant with the existing guidelines.

One potential approach is to a use camera system or 3D gesture trackers to track fine hand movements, identify user gestures, and so provide feedback to the user or a central management system, with the overall goal being an automated tool that can ensure compliance with the hand washing guidelines. However, in advance of developing these systems, preliminary analysis for detection of hand position and the associated motion detection was required. The aim of this paper is to track linear and circular hand movements using a camera-based approach, by extracting skin pixels and applying contours-centroid detection to the video frames.

2 Hand Gestures and Features

Hand Gestures are a natural mode of communication and are popular in the diverse areas such as sign language, aviation industry, music directions etc.

Hand Gestures can be of two types

1. Static hand pose: requires less computational power for processing
2. Dynamic hand movement: complex due to motion and direction involved

For the purposes of gesture tracking, a feature is a characteristic information of the local appearance of the object to be tracked [8].

Geometric features that have been used in the literature include those relating to the form and shape of the hand; such as distance, elevation, curvature, palm features, hand centre. Non-geometric features may also be used including colour and motion [9].

Features can be also classified as low-level and high-level features in the field of image processing and machine learning. [15]

Low-level features include elements such as lines, corners and edges of a hand. They correspond to the minor details of the object to be tracked. These features are useful for building an overall hand detection model.

High-level features are requires spatial information of the object such as fingertip position can be calculated or composed from low-level features. These include finger location and centre of the palm. These features can be useful in the classification of dynamic hand movements

Combinations of low-level and high-level features can be useful for modelling the overall gesture recognition system. Low-level features can be extracted from 2D images and high-level features can be utilised from low cost, low-power consumption- 3D sensors such as the Leap Motion Controller, and Microsoft Kinect [10].

Figure 1 demonstrates the sketch of hand features used for recognising various hand gestures and Figure 2 is the proposed setup for tracking hand-washing steps.

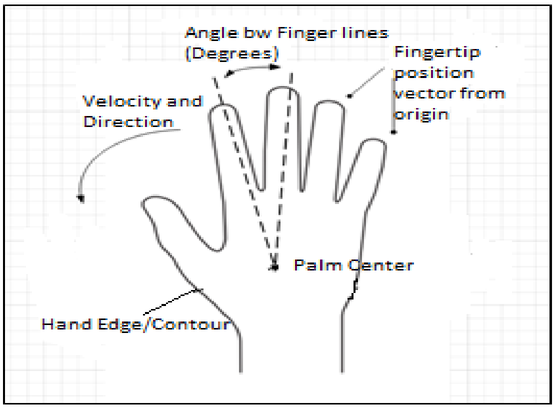

Figure 1: Low level and High-level hand features

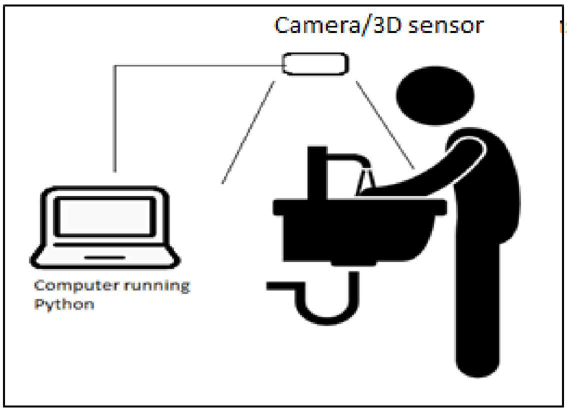

Figure 2: Proposed setup for Data acquisition

3 Feature Extraction for Hand Hygiene stages

Video-based observation is widely used by primary care researchers to analyze complex doctor-patient interactions and act as a source for a richer data collection process [14].We use a similar approach to understand HH patterns among health care workers and to identify the associated image processing features. Ten videos of healthcare professionals demonstrating WHO hand washing guidelines were sourced from the internet.

The unique human identifiable features that could be used to distinguish stages were carefully observed and extracted. Combination of these features can then be used to detect each hand washing stage. As the guidelines can still be interpreted differently, this had to be accounted for. Therefore, the corresponding human observed value for each feature and its occurrence is noted. This process was executed for all six-HH stages.

After visual inspection, the unique discriminating features were reduced to *1) Palm orientation, 2) Palm shape, 3) Finger spread, 4) Hand trajectory, 5) Rate of movement and 6) Stage duration.*

An example of extracted features for sample stage (Palm to Palm) is shown in Figure 3.

Stage	Features	Value	Occurrence
Palm to Palm	Palm Orientation	Facing each other (not facing each other)	10 (0)
	Palm shape	Flat (curved)	10 (0)
	Fingers spread	Straight and Closed (Straight and Open)	10(o)
	Hand Trajectory	Linear(Circular)	6(4)
	Frequency	Hertz	0.8-3.6 Hz
	Time duration	seconds	2 - 7 sec

Figure 3: Hand Features for 'Palm to Palm' stage through human observation

4 HH Feature -Hand Trajectory

While analyzing the video recording of the health care workers washing hands, it was found that the hand trajectory was either linear or circular as per personalized interpretation of the hand hygiene guidelines. In this paper, an attempt is made to track the hand trajectory from the video frames by utilizing the image-based approach.

Skin Detection is a process for finding skin colored pixels in an image or a video. In one of the earliest applications, skin colored regions were detected to identify nude pictures on the internet for content filtering [14].

In another application, skin pixels were detected to identify TV news anchors for video annotation and retrieval.

In such applications, video frames largely contain the face and the hands of the anchor and the indoor-background environment is controlled with hardly any skin-tone color related objects such as wood, which can be misclassified as skin [14].

The YCbCr color space was selected for skin detection due to

1) Its ability to separate the illumination channel(y) from two orthogonal chrominance channels (Cb,Cr) and

2) Its invariance to illumination intensity. Both characteristics make it appropriate for skin detection applications [14].

4.1 Skin detection technique using YCbCr- colour space model

The following steps were used in the skin detection technique for this work. Figure 5b) is the output of these steps.

```
1. Input frame is in RGB format
2. Input frame is converted to YCbCr format
3. Mask is applied within the range, 127>Cb>77 and 179>Cr>133
4. Gaussian Blur is applied to reduce the extra noise
5. The output frame contains only skin pixels. Save the frame.
```

4.2 Contour and Centroid Detection

Contour tracking is widely used in the field of image processing and has been applied to a diverse range of problems. For example, Xie et al. (2013) have used a contour detection method to determine the number of copper cores in multi-cored wire [11]. The idea behind contour tracking is to traverse the border of a region completely and to detect the edge points.

The open-source, computer vision library, OpenCV offers a `cvFindContours` function, which can retrieve contours from a binary image and return the number of detected contours.

Poda et al. (2018) computes the perimeter of a contour to detect specific shapes such as a Pentagon, and an initial classification character 'P' is saved and transmitted to an Arduino for the movement of a mechanical arm [12].

Bochkarev et al. (2017) compares object characteristics such as area, perimeter and compactness of the contour of regular shapes to that of irregular shapes using OpenCV [13].

The following steps were used for the contour-centroid detection for this work. Figure 5c) is the output of these steps

1. Input skin frame is in RGB format
2. Convert the frame to Grayscale format.
3. Gaussian blur is applied to reduce the extra noise
4. Thresholding is applied to the frame
5. Find contours in the frame
6. Sort the contours and find the largest contour.
7. Calculate image moments for the largest contour
8. Find x, y coordinates of the centroid
9. Display the frame with contour and centroid

5 Results

Figures 5a) to 5d) are the results of the algorithm explained in section 4. The overall work is focused upon tracking linear and circular hand movement in a natural setting. Two videos were recorded depicting linear and circular hand movement. Each frame of the video was transformed into an image. The images with hands were processed further to extract the hand, the largest contour and the subsequent centroid for the largest contour and the rest of the frames with background information were discarded.

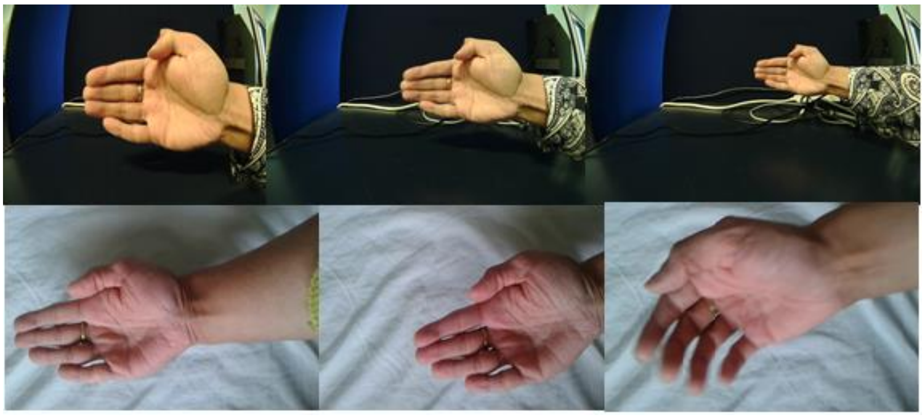

Figure 5a) Selected hand frames for linear and circular hand movement

Figure 5b) Selected skin frames for linear and circular hand movement

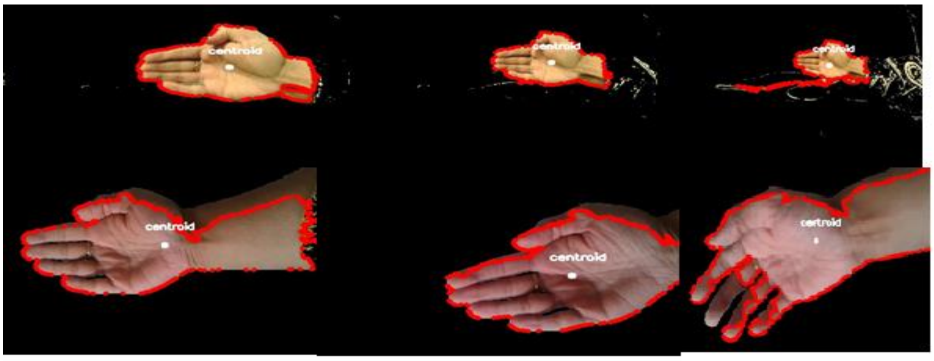

Figure 5c) Selected skin frames with the largest contour and the centre of the contour

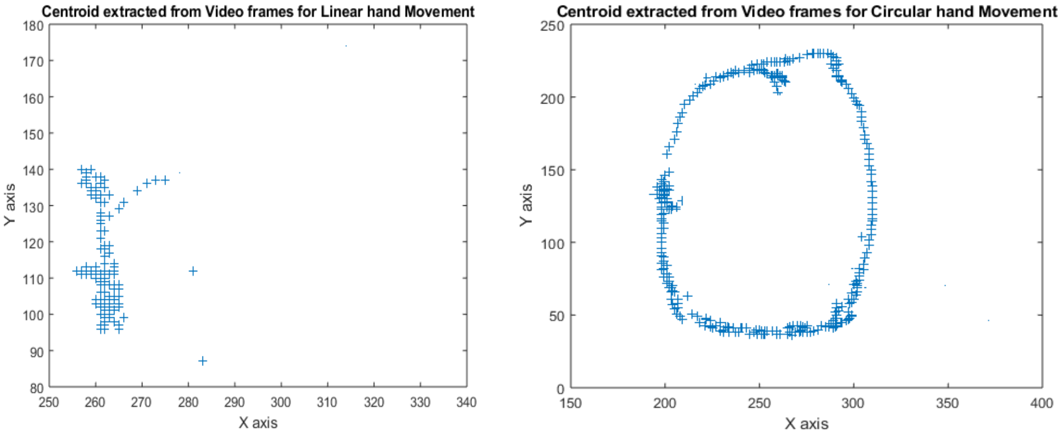

Figure 5d) Centroid-Plot for linear and circular hand movement

6 Conclusions

Hand trajectories such as linear and circular hand movement were tracked with the extraction of low-level features such as hand boundary from camera-based video frames with the use of the YCbCr colour space. This approach can be further integrated with a low cost-3D hand-tracking device such as the Leap Motion Controller for extracting high-level features such as palm-centre, fingertip position and palm-velocity. High-level features sometimes require high computing power when extracted from 2D video frames. Integration of camera-frames and 3D positional data from gesture trackers such as the Leap Motion Controller may be an optimal solution for building a successful hand-gesture recognition system. The future work will utilise Leap Motion controller for tracking hand trajectory and expanding the current work to include two hand movements in hand washing.

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