Joint Roughness and Wrinkle Detection Using Gabor Filtering and Dynamic Line Tracking

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Abstract

Skin quality analysis is a continuously increasing field for the detection of skin dryness, wrinkles and other skin conditions for the recommendation of skin-care products. Each method reveals valuable information on age, disease and general habits. Contributions are being made from companies, but many methods make use of extensive image data and diagnostic equipment that are too expensive to obtain. These would involve people visiting skin-care shops for a diagnosis, which is often time consuming and troublesome. A joint technique is proposed to locate skin roughness as part of an optimized wrinkle detection technique based on the capabilities of mobile devices without the use of diagnostic tools. The technique makes use of thresholding, shape analysis and dynamic line tracking for the analysis of skin roughness and wrinkles.

Keywords: Mobile Devices, Wrinkle, Roughness, Texture Analysis, Line Tracking.

1. INTRODUCTION

Mobile devices have advanced in terms of imaging sensors and can acquire high-resolution images containing skin texture [1]. Some of these devices reach up to 48-Megapixels and allow for HDR capturing for light correction. These capturing capabilities are sought out when people buy devices [2], proving viability for skin-care services to be made available. Many similar techniques rely on diagnostic equipment designed to block out external light sources [3][4][5] and improve the accuracy of the algorithms. However, the aim of this paper is to prove whether wrinkles and roughness can be analysed using similar techniques, only using macroscopic images. Such an advancement would be beneficial for skin-care companies, allowing for user convenience when diagnosing subtle skin conditions. Wrinkle detection methods including Hessian Line Tracking (HLT) [6] and Gabor Wrinkle Detection [7] produce excess data relating to skin roughness and are viable starting points to building a joint wrinkle and roughness technique. Except neither of these papers go in depth on whether this data can be captured accurately.

Recent techniques such as CNNs [8] are proven to have unseen accuracies and processing time compared to standard techniques. However, such algorithms require massive amounts of relevant image data to train an algorithm correctly. While there is some wrinkle data available through datasets [9], it is still unreliable to develop texture analysis techniques through deep learning. Therefore, this paper focus on utilising HLT and capturing excess skin roughness data with changes including thresholding and dynamic line tracking for the tracking of vertical, horizontal, disconnected and unlikely shaped wrinkles.

1.1 Discussion

The detection and analysis of skin lesion through medical imaging has gained further attention because patient screening is not always an efficient way to diagnose patients [10]. Unlikely issues are often left undiagnosed for longer periods of time leading to a misdiagnosis and thus untreated medical issues. An age estimation technique [11] has been proven to estimate age at a higher accuracy than people. Making it far more efficient for algorithms to be used instead of people in some scenarios. The development of an algorithm capable of accurate skin analysis allows for infinite amounts of people to be professionally diagnosed from regular to severe skin issues and given the correct medical attention efficiently. Even though this discussion would normally be held for the detection of cancers, the analysis of wrinkles and skin quality provides valuable data on ethnic groups, gender, age and life style [12]. Showing the importance of discussing all forms of skin texture analysis techniques in regard to medical imaging.

Common issues within texture analysis is lighting quality, even a slight difference in light could harshly affect the results of any algorithm making it extremely difficult to locate edges and texture detail. It would be complete insanity to program an algorithm capable of analysing texture detail in all possible lighting conditions, but assumptions can be made for subtle effects. One paper estimates illumination [13] to avoid the use of diagnostic tools with an accuracy of 75%. However, to achieve higher accuracies specialised tools must be used to block out lighting variations [14][3], which allows for increased accuracy and simplicity when developing the algorithm. Furthermore, skin can have an infinite amount of abnormalities [15] regardless of lighting conditions. As such, the main focus is the detection of skin roughness and avoiding abnormalities such as freckles, spots, skin pores that might affect the results.

Wrinkles remain a dominant feature and are less affected by noise than skin texture detail. As such, there has been a large increase in the amount of dermatology companies [12] that are making use of age estimation techniques [16] for the advertisement of antiaging products. An algorithm capable of recognising skin roughness means that companies can efficiently diagnose people on skin quality without having to hire a professional dermatologist. Including this, such algorithms are fundamental to the development of medical companies in the aid of locating skin dryness, which is caused by an over consumption of alcohol [17] and an increased depth or amount of wrinkles is associated with smoking [18]. The analysis of such data has vast uses in allowing for faster diagnoses in general health and well-being.

1.1 Datasets

When testing the accuracy of the algorithm the Bosphorus [19] dataset is utilised for a comparison against HLT. Within this paper it is assumed that the person using the algorithm would attempt to use it in decent lighting conditions and is facing forward. Ignoring extreme scenarios of hard shadows and specular reflections. As such, Bosphorus is an ideal dataset for testing as it contains high-resolution images alongside moderate changes in light intensity.

Facial features would greatly affect the results, therefore the landmarks within the dataset are used to remove the eyes, nose, mouth, eyebrows and other anomalies. Similar to a study that generated a mask to hide facial features [20] for Hybrid Hessian Filter [21], which aided in improving the results of the tests. Removing these features proves the algorithm works under certain conditions and aids in proving the accuracy of the algorithm. The only difference is that the tests take place within the whole area of the face instead of only the forehead, which many wrinkle detections including HLT papers use.

2. METHOD

Wrinkle detection is a tool often utilised for automatic age estimation and is still considered a contemporary topic for study[11]. These methods are split into two categories. The first is utilised through Facial Aging Patterns (AGES) [22][23]. The aim of AGES is to break down facial appearances and age manifold [23] to generate patterns through machine learning that can be compared to estimate age using the wrinkle data. These techniques do not provide an exact wrinkle location, but their accuracy for estimating age is comparable to the accuracy of humans [11]. As specified earlier it is unlikely that enough images can be obtained to train a pattern for this reason and this does not provide the exact wrinkle data, therefore it is not used.

The second type of technique makes use of linear filters [12][6][7] using similar techniques to Gabor [12][23] or Frangi [21] filtering to break down the image into a three-dimensional form allowing for depth and texture to analysed without the use of specialized cameras. Following this is a threshold or morphology technique capable of estimating the location of wrinkles. To prove the wrinkles have located a line tracking algorithm takes place on the non-linear structure. Ideally line tracking is not used, but it was found to heavily increase the accuracy of HLT [6] and generally aids in proving the following rules [7]:

- Non-linear structure – A single curved line that fits within the wrinkle, wrinkles are almost never a straight line due to the curvature of the human face.
- Disconnected – The majority of wrinkles do not intersect and are therefore disconnected from one another because of the creases in the skin.
- Smooth – The wrinkle should have moderate length and thickness, as such much smaller wrinkle details are likely to be ignored.

Gabor wrinkle detection [7] already shows promising results for the detection of skin roughness compared to HLT. The filtering technique leaves anomalous data that is subsequently ignored by the line tracking algorithm and leaves enough skin texture data intact for the detection of skin roughness. Therefore, Gabor Wrinkle detection is followed closely. Overall the algorithm produced makes use of linear filters, specifically Gabor, thresholding and line tracking for the detection of wrinkles and skin roughness. One of the main focuses is a dynamic line tracker similar to HLT with the capabilities of rotating in any direction unlike the other method that focuses on the detection of horizontal wrinkles.

2.1 Filtering

The first step in many computer vision-based algorithms is to break down the image and remove or expand on details in the image for later processing. For example, the image is converted from a traditional BGR image to a grayscale as the colour data is not needed for the rest of the algorithm. Preparing the image is generated through filtering, modifying colour and resizing, these methods are described throughout this section.

Lower resolution images have smoother transitions between edges and higher resolution images have an increase in gradient variations. As such, before using edge detection methods, the data should be Gaussian blurred depending on the resolution of the image. By smoothing the image using a Gaussian kernel, edge detection techniques detect less anomalies [24] and only the most distinct lines or edges. The well-known technique called SIFT goes under the same premise of locating distinct features by periodically applying a gaussian kernel. This allows for scale variant comparisons between features regardless of image resolution. Blurring the image removes some data that could be used for skin roughness; however, a slight blur only affects the less distinct skin anomalies that are far too small for analysis. It is unlikely this particular style of algorithm can be made scale variant, therefore the algorithm must be developed with similar resolutions of image same as many similar algorithms [6][7].

Gabor filtering is considered a versatile technique, ranging from medical imaging techniques [25], finger print biometrics and face detection [26]. It is a common application used for increasing the quality of texture [12][27] for skin analysis and wrinkle based methods. Multiple Gabor filters are defined with different representations in gradients which are stored in a Gabor Filter bank, which are then added to a single image (Figure 1). Once the filters have been applied these reveals three-dimensional data regarding skin texture that is normally invisible to the human eye.

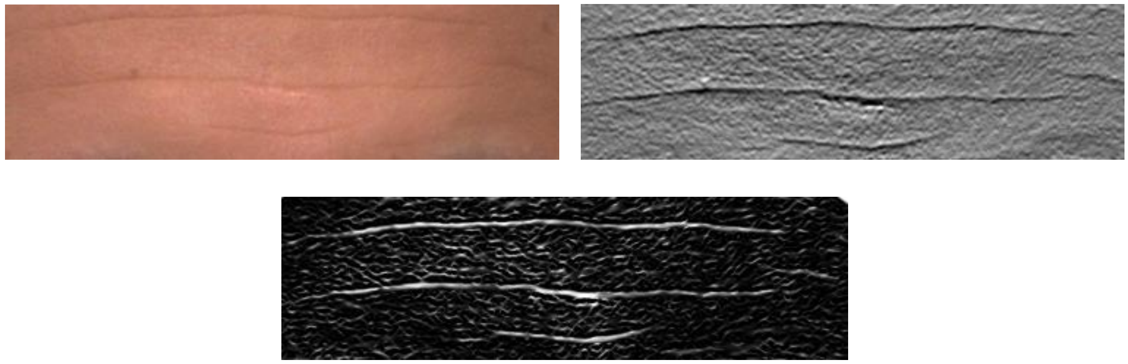

FIGURE 1: Steps for the filtering process (a) original, (b) Gabor filtered image, (c) Gabor filtered followed by Frangi filter

The versatility of the technique is rather the downfall of Gabor filtering, because it enhances large amounts of anomalous texture data within the image making line tracking and other algorithms difficult to implement. To get around this problem Gabor Wrinkle detection [7] makes use of a technique called Marked Point Process [12], which effectively locates lines within a Gabor filtered image through morphology and returns these distinct lines without any of the anomalous data effecting the results. The located lines can be later analysed for curviness to prove whether the line located is a wrinkle. That excess data allows for skin analysis techniques to locate skin roughness without another process being developed for locating that texture data at a later date, therefore allowing for the analyses of wrinkles and skin quality within the same algorithm.

Frangi filtering is considered an equally powerful choice designed for medical imaging [28], but only locates lines and removes the excess data. This is the technique of choice in Hybrid Hessian Filter for that specific reason. The only downside is the technique is much slower than other linear filtering techniques, but the results are easily worth it.

2.2 Thresholding

Distinct wrinkles are disconnected and cracked areas of skin that vary in texture detail compared to the area surrounding a wrinkle [7]. Typically, deeper wrinkles lack in texture making it easier to locate them over light wrinkles that retain some form of texture that makes it much harder to detect. With this in mind a technique has been developed that compares the variations of gradient in a line to locate shapes within an image that are lacking in texture detail. Naturally such an algorithm would capture distinct lines and excess detail captured through Gabor filtering, this excess data is used for calculating skin roughness as seen in Gabor Wrinkle Detection [7].

The thresholding method itself (Figure 2) searches for vertical lines of gradients that are subtracted against the center point in the image, each value on the y-axis is compared to the center point and if it is below a threshold then the center point increases in score. Therefore, any area that lacks in texture detail and are surrounded by an edge are saved to a separate image file in preparation of roughness detection and line tracking. Skin roughness data appears as smaller cracks around the area of the skin, but too small to be defined a wrinkle.

This algorithm searches for lines within the y-axis instead of the x-axis which reveals horizontal lines more so than vertical lines. Wrinkles intersecting is extremely rare but the algorithm designed this way to avoid intersections that could be generated when utilizing both axes, in which the line tracking algorithm and therefore the detection of wrinkles would fail. Currently the depth is pre-defined but the algorithm works in such a way that it locates lines of any thickness up to a specified size, therefore it would have to adjusted depending on the resolution of the face and image. During this thresholding process darker areas generated through Gabor filtering are added to the image as gray lines and lighter sections are added as white, which could be used to estimate the depth of the wrinkle.

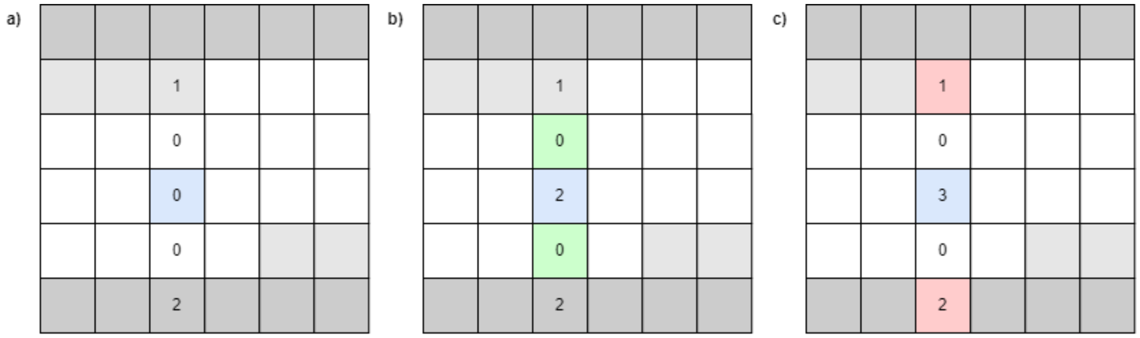

FIGURE 2: Representation of the thresholding method used for locating wrinkles and skin roughness data. The blue pixel represents the current pixel and red/green represents the pixels being compared to the center point. A score is gained for the blue pixel each time the green/red values are below a threshold.

The thresholding process as expected leaves many anomalies which can be easily removed using a blob detection algorithm, but in this case, it is saved and utilised to calculate skin roughness. The blob detection algorithm essentially locates the size and shape of separated blobs and removes them according to size. As long as the width and height are congruent and the blob is similar to the shape of an oval, then it is moved to a separate image and is later used to calculate the skin roughness.

The skin region would not have any blobs if the skin was not rough, therefore the example below (Figure 3) shows the skin roughness data with and without skin roughness. Compared to someone with perfectly smooth skin it would be a black plane with little to no blobs within the area, this could be used to show particular rough areas of skin on a face.

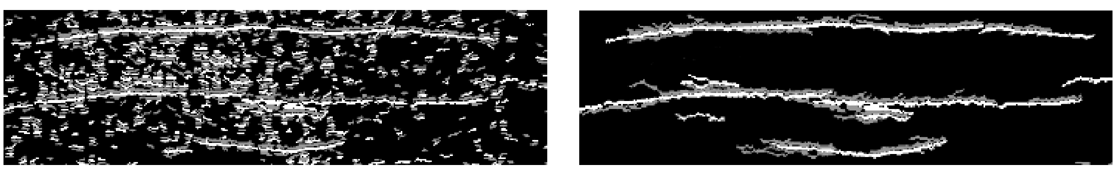

FIGURE 3: Thresholding technique once used on wrinkles, image (a) shows the method when the blob data has not been removed, (b) shows the wrinkle location once the blobs have been removed.

2.2 Line Tracking

Wrinkle detection is commonly implemented through line tracking [12][6][7], this locates false positives and, in turn, proves whether the located line is a wrinkle. For faster tracking, geometric constraints could be utilised to mark points of interest during morphology [12]. Non-linear lines can be best fit compared to the geometric constraints. Once the line has been tracked the curve of the line defines whether it is a wrinkle. Before applying the wrinkle detection method, the data surrounding the wrinkles would be removed using a simple blob detection technique. Removing all the blobs decreases the process time and improves on the results when line tracking.

The developed line tracking method (Figure 4) is based off HLT except it is built to track lines and locate positions similar to the rasterization process of generating graphics. Line tracking without such methods means drawing with grid constraints leading to errors depending on shape, thickness and rotation of the wrinkles, although this is hardly a problem for tracking on wrinkles on the forehead because they are almost always vertical. This current method allows for further control in orientation when tracking the line and allowing for accurate line tracking for some of the most unlikely of wrinkles.

Tracking lines without grid constraints involves the use of a technique called Bresenham that is commonly used for rasterization of geometric positions in the generation of graphics. The algorithm is designed for locating the nth values that are located between two points on a grid, allowing for a massive amount of orientations (currently 64) that the line can track towards. Bresenham has many alternate versions built for different means but the base technique is exceptionally easy to implement and to understand compared to some of the advanced versions, therefore the base version is used.

Circles are a fundamental part of generating shapes and lines within an image, in this case sin/cos calculates the area of a circle and can be used to aim Bresenham in any direction regardless of pixel locations. This is important because it allows for line tracking to continuously move in that direction regardless of the grid constraints, unlike Hessian which has a set number of positions that the line can travel in. Once the line has been drawn to the edge of the circle an angle is chosen at 90 and -90 degrees to count towards the edges of the line being tracked. Depending on which line locates an edge at a shorter distance defines the direction that the line turns to avoid going out of bounds. The line tracker continues until it reaches the end of the line, the line data is then saved for analyzing the curve of the wrinkle, therefore proving it is a wrinkle.

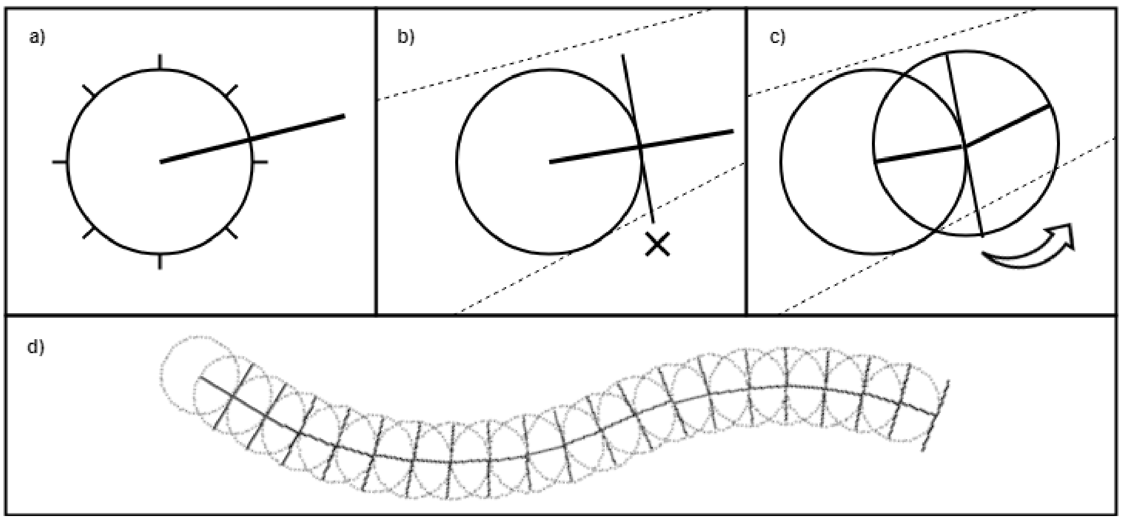

FIGURE 4: Explanation to dynamic line tracking, (a) demonstrates the circle that can be used to choose the orientation the line tracks in, (b) shows an intersection found through Bresehman marked as an ‘x’ which demonstrates it needs to turn (c) the line changing direction because the intersection and (d) demonstrates what the line tracking looks like on a larger scale.

When tracking there are multiple chances for the line to go out of bounds, this is to aid in locating disconnected and hard to track lines that are partially incomplete or noisy because of the original quality of the image or the thresholding process. Therefore, it traverses over gaps and connects wrinkles that would otherwise be counted as separate wrinkles which would affect the results.

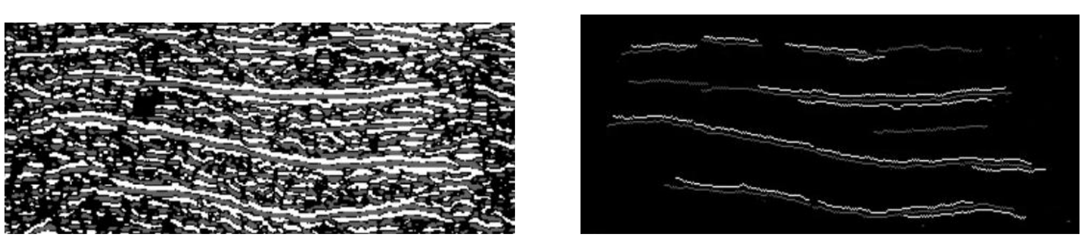

FIGURE 5: Line tracking accuracy after removing skin roughness data.

2.3 Roughness Detection

Detecting skin roughness derives from a visual inspection by a professional dermatologist with extensive training and experience. Nonetheless, even trained dermatologists can miss some intricate details, hence why there has been an increase in computer-vision related dermatology algorithms designed for skin analysis [29]. Traditionally, human skin analysis is used purely for dermatological imaging tools [30], but seeing a dermatologist for professional skin care advice that is not serious, would be troublesome for many people. Therefore, it would be convenient to have a fast skin roughness technique built for mobile.

Wrinkles have a distinct curvilinear structure [7] allowing them to be detected regardless of image quality, expect skin roughness is intricate and much of that detail could be lost in varying lighting conditions. Thus, they are harder to locate and are dependent on the quality and conditions the image is taken under. Unlike many skin roughness techniques [30][31], a full size images are used instead of small patch of skin. In the proposed technique there are certain advantages to using a full-size image, the whole face will be analysed which will show specific dry patches, although this could show detail from anomalies data such as facial hair, blemishes, spots, etc.

Roughness detection has a number of different skin factors that must be analysed, these are anomalies, aging [14], humidity and care products [32]. To get perfectly accurate skin roughness all the existing factors would have to be considered. The technique works well with soft shadows but specular lighting makes the indentation more intense than it normally is, effecting the results. Recent specular removal algorithms [33] could negate and improve on accuracy. This would likely make the process too heavy and might increase the chance of abnormalities.

The previously filtered image (Figure 6.b) contains all the data needed to check for rough patches of skin. A kernel is passed over the image that accumulates a score of the depth and size of the blob or wrinkle. In this case, the gradient data represents rough skin and as such score will be added up within those areas. Gaps between these gradient changes result in there being less score within that area. The image shown in (Figure 6.c) shows rough patches of skin, as a visual representation of the data.

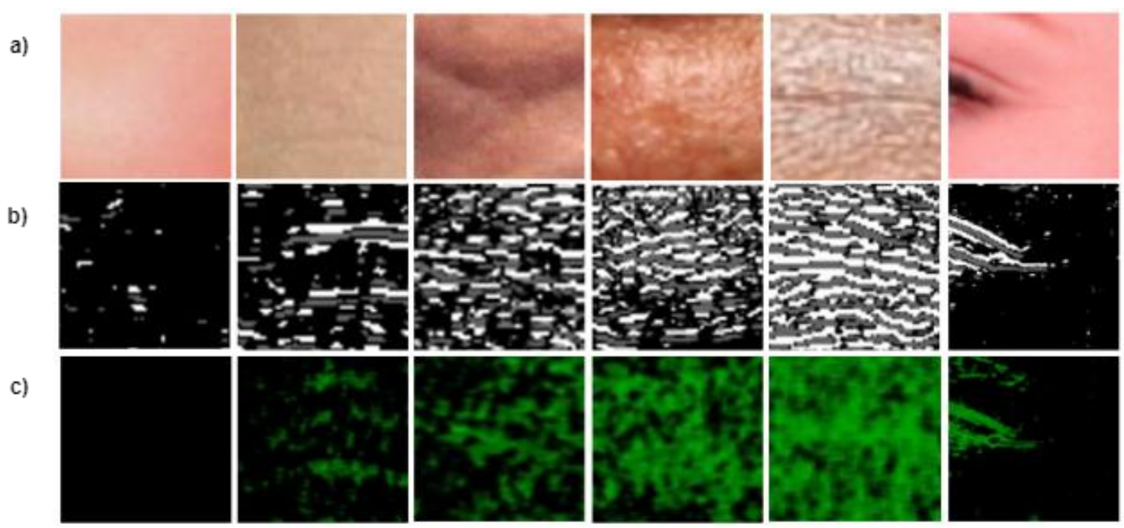

FIGURE 6: Images from the IMDB dataset[19] demonstrating different roughness depending on skin quality, (a) Original image, (b) After thresholding method and (c) after roughness estimation.

3. COMPARISON

Overall the proposed algorithm shows promising results when tracking wrinkles in the Bosphorus dataset. With an accuracy of 80.09%, compared to HLT with an accuracy of 87.75%. As proposed in this document, Gabor filtering was utilised on its own, but was found to be sensitive when changing lighting conditions, effectively lowering the accuracy to 39.46%. However, Frangi filtering increased the processing time by 2560ms on mobile devices, it remains a necessity to normalizing the wrinkle data in this algorithm. This makes the technique increasingly similar to HLT, except with revised thresholding and line tracking.

The accuracy suffered by 7.66% when using the Dynamic Line Tracking algorithm instead of HLT, but allows for the tracking of vertical, horizontal, disconnected and unlikely shaped wrinkles. There are benefits, such as a decrease in processing time. Unlike HLT and Gabor Wrinkle detection vertical wrinkles can be tracked without re-initiating the whole algorithm on a rotated image. Allowing for some of the most unlikely shaped wrinkles to be located and aiding in the optimization for mobile devices with a speed of 3960ms. With the changes made to filtering that improves the accuracy in many lighting conditions the processing time increases to 6520ms in the respected resolution. This is suitable considering it is built for mobile devices and does not use any high-end GPUs.

While the technique itself can successfully detect skin roughness it is highly sensitive to changes in the light direction and intensity. Considering the algorithm is designed for a mobile environment in mind, there is no control over the environment it is being taken in. Therefore, the data is ambiguous and to obtain a reasonable accuracy the technique should be utilised in a closed environment. It was attempted to use specular reflection removal [33] to clean the results, however texture details are vulnerable to noise [30] and often worsens the results.

4. CONCLUSION AND FUTURE WORK

Overall the algorithm shows promising improvements in tracking disconnected, vertical and horizontal wrinkle data within the Bosphorus dataset with an accuracy of 80.09%. Alongside the optimisation for mobile devices. It is proven that skin roughness can be implemented within HLT. However, the algorithm is less versatile and is greatly affected by lighting conditions. This means that companies can allow for wrinkle detection data to be gathered from a range of environments and lighting conditions. Although, for the analyses of skin roughness the algorithm should be utilised within a closed environment. Future work involves estimating the illumination of skin texture to remove or enhance details, increasing the accuracy of skin roughness in a range of lighting environments.

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