Diagnosis and Management of Hand Arthritis
Using a Mobile Medical Application

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ABSTRACT

A deployable mobile medical application is presented that employs a smartphone camera, patient input, internet connectivity, and cloud-based image processing techniques to document and analyze physiological characteristics of hands in osteoarthritis (OA) patients. The application performs digital image processing that spatially calibrates the image, locates hand fiduciary features, and quantifies hand features to identify abnormal distal and proximal interphalangeal joints. The algorithm determines the finger centerlines and joint coordinates. From these anatomical fiduciary points, it measures the width of fingers, location and size of joints, and finger joint angulation. The diagnostically relevant features measured by the mobile application can be applied to current diagnostic protocols such as the American College of Rheumatology (ACR) criteria for OA. Based on the results from a pilot study, the mobile application was modified to include interactive user guidance built into the smartphone. This app makes improvements on the algorithm that validate the image quality and makes the algorithm less dependent on precise capture conditions. Based on clinical feedback, a web-based portal and dashboard for advanced analysis was developed and presented. Clinicians, researchers, and patients can use this to explore relationships between pain, treatment, environmental parameters, and lifestyle factors.

Keywords: osteoarthritis, hand joints, articular cartilage, image processing, computer-assisted validation studies

1. INTRODUCTION

Many chronic diseases including muscular-skeletal disorders like arthritis and chronic back pain, skin conditions like acne, psoriasis, rosacea, and eczema can slip through the cracks of an overburdened health system, and the onus for managing the disease then falls to the patient. Ongoing discomfort and the desire for better treatment motivate these patients to seek an alternative to the conventional health care system. Mobile health applications, including telemedicine, may help reconnect these patients to the health care system in a cost-effective way. These apps can guide the patients in recording and analyzing the impact of environmental conditions, lifestyle and treatment on their condition so they and their clinicians to determine what will work best for them. In developed regions, mobile health (mHealth) can help patients to reduce fees, often charged against their medical insurance deductibles, as well as the time and expense of commuting to clinics. In emerging regions, mHealth can provide low-cost alternatives to, or guidance on, contacting a physician. Mobile is the most widespread communication infrastructure in the world. Much of the global population has access to some form of mobile communication, even in the most remote areas of Africa, Asia, and Latin America. This infrastructure offers societies the opportunity to transform their healthcare services.

By applying modern algorithms that can calibrate and control smartphone cameras we can quantitatively measure size, shape and other characteristics of human anatomy. An example of a chronic disease condition which affects human anatomy and also has a symptomatic effect on patient is arthritis.

Osteoarthritis (OA) is one of the most common joint disorders in the United States [1]. OA prevalence varies depending on which definition of OA is applied, which specific joints are being considered, and population demographics. After
radiographic knee OA, radiographic hand OA is the second most prevalent, e.g. 27.2% among the Framingham study participants [1]. The distal interphalangeal joints (DIP), proximal interphalangeal joints (PIP), and the carpometacarpal joint of the thumb (CMC) are the primary sites of hand OA [2]. The social and economic impact of OA is likely to be of more concern over the next few decades since due to increased longevity more than 80% of the population can expect to live beyond 75 years [4].

Hand OA affects the ability to perform everyday tasks and this can reduce the quality of life of those living with OA. The pain, aching and stiffness that limit the ability to perform these tasks are considered to be symptomatic OA [3]. Symptomatic OA is a subset of radiographic OA, which measures by joint space loss, osteophyte formation, and cyst formation [2]. Prevalence of radiographic OA is about 60% at age 60, yet the prevalence of symptomatic hand OA is about 6% for women and 3% for men at age 60 [5] (6.8% in Framingham subjects [1]) which is much lower than the specificity rate diagnosed by x-ray. This calls into question the utility of x-rays for confirming osteoarthritis. Moreover, radiographic assessment increases patient radiation exposure, is more costly, and depends on availability of expert radiologists for interpretation. More importantly the development of radiographic features such as osteophytes and joint narrowing occurs over a considerable length of time, resulting in lower accuracy for younger symptomatic OA patients, a potential future target group for preventative treatment [6][7]. The most recognized method to score hand OA is by physical examination and assessment using the American College of Rheumatology (ACR) criteria [2]. Like radiographic assessment, one of the disadvantages is difficulty standardizing the assessment due to subjectivity and limited availability of expert clinicians[8]. Recently, it has been shown that hand photography can offer a way to both record and standardize interpretation of hand OA severity [9]. Classifying hand OA this way is simpler and more affordable than radiographic assessment, facilitating larger population screening as well as remote assessment [9].

As part of the AGES-Reykjavik study conducted in Reykjavik, Iceland, a large number of digital photographs of elderly subjects (160 males and 221 females aged 69-92) with hand OA were assessed by experts and an atlas of scored hand OA pictures was developed [10]. The standardized hand photographs showed good intra- and inter reader reliability, and the photographic hand OA scores were correlated with both clinical and radiographic hand OA assessment [10]. This study was later extended to see if the atlas would be as useful for younger populations. The atlas and method created in the Iceland study was used with patients in Keele, UK and results of the study were published in 2013 [11]. In the study, the atlas developed was used to assess 558 participants who were community dwelling adults 50 years of age and older. The scoring system was shown to be reliable and a good indicator of hand OA [11].

In order to optimize comparison of hand photographs to the photographs in the atlas, tight constraints were placed on image capture, including specific hand position and camera distance. Having a consistent setup like this in different clinical settings could create barriers to adoption. However, since the time of the study, digital cameras of high quality have become embedded in smartphones, methods of spatial calibration for digital images have evolved and data transfer speeds have increased significantly, enabling cloud-based image processing. If the qualitative features used in the AGES study hand atlas can be quantified, then they can be employed in a smartphone-based assessment protocol to identify and stage hand OA. In this manuscript, we describe our work toward implementing such a system for automated scoring of hand OA.

Most mobile health apps that are available in app stores and address OA, provide reference tools for clinicians [12], patient education tools [13] and/or telehealth tools for remote consultation [14]. We are developing a mobile health app which comprises measurement, data collection, health record, and reporting systems, as a single medical device to facilitate communication between patient and clinicians.

2. METHODS AND MATERIALS

2.1 System architecture

The mobile application that we have developed (myHand) turns a smartphone into a medical imaging and management device for hand OA. The mobile application facilitates fast entry of pain levels, treatments, and other lifestyle and environmental data (e.g. weather, diet, and activity) to record the patient journey of those living with arthritis. The system can provide reports for individuals, clinicians, and caregivers that may help identify aspects of patient lifestyle that make their arthritis better or worse and let them compare effectiveness of different treatments to find what works for them. The system consists of three distinct parts: 1) the mobile application that acts as an interface for the user, facilitates image capture, creates patient profiles and displays analytical results, 2) the cloud server that stores patient profiles,
provides image, and 3) data management and performs image processing as shown in Figure 1, and the web portal which provides more advanced review for clinicians (or patients).

The mobile application uploads hand images, patient input data and other smartphone information such as GPS, and sensor data. It also provides user guidance, processed data and clinical reports from the cloud server. New users create profiles that comply with electronic health record standards. We use the default onboard camera of the smart phone to capture images of a subject’s hand. We know people will always take pictures differently and under various lighting conditions. The image processing methods attempt to minimize these dependencies on image capture conditions; however several constraints are required, including providing a single sheet of white paper in the background of the hand. A standard letter size or A4 sheet of printer paper is required. The hand needs to be placed on top of and inside the boundaries of the paper. The hand should be oriented orthogonal to the paper. The mobile app detects the border of the paper and provides visual feedback to the user when the hand and paper are positioned correctly.

The cloud image processing checks for the correct positioning of the paper and then it checks whether the image is focused. It identifies the corners of the paper and uses those and the a priori knowledge of the paper dimensions to remove lens and perspective distortion and to spatially calibrate the image to real-world dimensions. The calibrated image is then used to identify key anatomical features of the hand including finger tips and vertices and to measure hand geometry including finger and joint thickness and finger segment angulation. This data is then used in hand analysis following which reports are presented through the either the smartphone or web portal interface.

2.2 Digital image processing for hand anatomical analysis

Figure 2 shows the image processing process used in the myHand hand analysis algorithm. It includes five main processing steps and three error checks. When errors occur in processing, an output error message is generated to suggest a likely cause of the problem that can guide the user to capture another image. The error check steps identify if the error was caused during paper detection, hand border detection, or finding the fiduciary points in the hand image. The image processing steps are described in more detail below and error check examples are described in the results and discussion section.

2.2.1. Spatial Calibration

A standard sheet of white paper (letter size or A4) placed beneath the hand aids the image segmentation process by serving as both a reference object with known dimensions that helps calibrate the spatial features of the image, and as a reference object with a known color characteristic to calibrate the color of the image, if required. The initial phase of processing is paper edge detection in which the color (RGB) image is converted to two grayscale mappings: the average intensity map, and the standard deviation map derived from the three color values of each pixel in the RGB image. The white paper region can be segmented by thresholding the two maps since white paper has relatively higher average
intensity in the average intensity map and lower variability in the standard deviation map. After the paper mask is created, a Hough transform algorithm is used to identify straight lines in the image corresponding to the edges of the paper object placed beneath the hand. The intersection points of the paper edge lines are determined and used to define the coordinates of the corners of the paper.

Figure 2. Image processing block diagram for hand analysis.

Once the paper corners are located, the image can be spatially transformed to the correct aspect ratio for the type of paper selected and the image pixels can be calibrated to real world dimensions. We are using the “cp2tform” function from MATLAB to infer a spatial transformation from control point pairs. The TFORM structure provides an inverse mapping from output space (x,y) to input space (x,y) according to the transform type (i.e. projective). The control point pairs include the four points of the paper corners from the original quadrilateral shape and the corners of the pre-known rectangular shape with the same aspect ratio of the paper type. After creating the spatial transformation function (TFORM structure), all the image pixels are transformed to the new coordinates using the “imtransform” function in MATLAB. The result of the image transformation is a new spatially calibrated hand image, independent of projection angle and camera distance to the subject.

2.2. Hand Segmentation and Analysis

The next step is segmentation of the hand from the white paper background and detection of the hand boundary. For lighter hand color, we used standard thresholding methods on the mean and standard deviation of RGB intensities. The hand regions have lower mean intensity values and higher standard deviations compared to the surrounding white paper. For darker skin we transformed the image from RGB color space to CIE 1976 L*a*b* color space and thresholded the chrominance a* and chrominance b* maps for hand segmentation. The L*a*b* color space thresholding is also more effective in hand images with shadows [15].

After hand segmentation, the boundary was determined by a MATLAB boundary-tracing function (bwbounary) to generate a linear array of sequential hand boundary pixels. The boundary pixel data was analyzed to identify the hand fiduciary points; specifically, the finger tips and the finger vertices. These fiduciary points enabled us to label and isolate each finger for independent processing including the extrapolation of the finger centerline. We used the centerline and
the finger boundary to quantify finger thickness and joint angulation. We analyzed the angle of a finger segment (phalange) by determining a best linear fit through the data points of the corresponding finger centerline segment and determining the deviation of the angle from the expected values for a normal finger.

We can measure true thickness of the finger at the joints and other locations and compare with physiological values standardized in the OA atlas provided by the Iceland study to identify abnormalities that may indicate the presence of OA.

3. RESULTS AND DISCUSSION

3.1 Cloud based image analysis and feature extraction

Figure 3 and Figure 4 demonstrate hand analysis using a digital image of a hand captured with a standard sheet of white paper (letter size for Figure 3 and A4 size for Figure 4) in the background. As mentioned above, this sheet of paper, placed beneath the hand, provides a spatial calibration reference for the hand image. The measured dimensions of the paper boundary are paired with known dimensions of standard paper for defining the spatial transformation of the image to real world coordinates. Figure 3(b) and Figure 4(b) show the paper edges and corners detected by Hough transform. Figure 2(c) and Figure 3(c) show the calibrated and spatially corrected images of the hand and paper. The images are cropped to the boundary of the paper. The distances between the pixels now correspond to real world measurement units (i.e. 100 pixel distance equals 1.27 mm). The next steps are the segmentation of the hand from the white paper background of the now calibrated image and the detection of the hand boundary. Again as mentioned above in the methods section, the boundary pixel data was analyzed to identify the hand fiduciary points; each fingertip and the finger vertices as shown in Figure 2(d) and Figure 3(d). We used the centerline, finger boundary and other fiduciary points to quantify finger thickness and to identify and measure other anatomical features such as joint location and interphalangeal joint angular deviation. Figure 2(e) and Figure 3(e) show the hand analysis results including fingers’ centerline, angular deviation of each DIP and PIP joints, location of DIP and PIP joints, and hand boundary.

Rather than develop a separate processing algorithm for locating fiduciary points for different hand orientations (right/left and palmar/dorsal), we flip the image horizontally so that the analysis always takes place with the thumb to the left and then the correct image orientation is restored following processing as can be seen in Figure 2 and Figure 3.

![Image](a)

![Image](b)

![Image](c)

![Image](d)

![Image](e)

Figure 3. myHand analysis with light skin color and letter size paper.
Figure 4. myHand analysis with dark skin color and A4 size paper.

Figure 5. myHand image quality validation.
3.1 Cloud based image quality validation

The current algorithm has multiple checks to ensure that a good quality image was acquired. Two of the main checks occur right after it has discovered what it determined as the four corners of the background paper. The first check is to make sure that the corners were found correctly.

The algorithm checks if the line that connects each corner of the paper around the perimeter follows along an edge of the paper. The algorithm accomplishes this by creating 4 lines, one for each edge, and then dilating each line so that the thickened line covers more area, centered on the edge (Figure 5a and Figure 5c). The thickened line is converted to a binary image that functions as a mask that can be overlaid on the binary mask that was created when the paper was originally segmented. The thickened line mask is used as a Region of Interest (ROI) on the segmented paper mask. A histogram analysis is performed for each line to check that the proportion of masked and unmasked pixels within the region of interest is around 50/50 (Figure 5b). The algorithm interprets too much of one type of pixel as an indication of poor corner detection (Figure 5d).

The second main check is whether the image is out of focus or is affected by motion blur. It begins similarly to the corner detection check in that it first creates a line between the corners, along the edge of the paper. Then the algorithm chooses a single point along that line and creates another line perpendicular to the paper’s edge spanning around 50 pixels. It uses this new line on the greyscale version of the original image and takes the numerical derivative. A sharp image will have a steep slope at the point of the line corresponding to the paper edge, whereas an out of focus or blurry image will have a more gradual change at the paper edge. The algorithm checks for a specific slope threshold, and interprets any image with an edge below that threshold as being too blurred to accurately report measurements (Figure 5e-g).

Figure 6. myHand app based user guide.

3.2 Application-based user guidance and report presentation

The myHand app requires users to take pictures with all four paper corners present in the image. However, in pilot testing, we observed that many users did not follow this requirement, possibly because people might have skipped the instruction pages or not realized the importance of the paper corners. In addition to improvements to the image processing algorithm to make it more robust we also needed to improve the user guidance. Our solution was to provide a
feedback based user interface, in the camera view, that guides the users through the image capture session. We placed a paper-shape overlay on the camera video feed that changes colors between red, yellow, and green depending on whether a piece of paper with all four corners are presented inside the rectangle overlay’s frame. Red means no paper is detected; yellow means the algorithm might have found something that looks like paper; green means the paper is detected. Since the paper is rectangular, simple edge and corner detection algorithms are used.

Based on user and clinical feedback we wanted to reproduce a report mechanism that was more responsive to user needs than our original simple HTML page. We wanted to include a friendly user interface, as well as easy extension and modification abilities and decided to move away from a basic HTML document. The new hand report view is purely native so that it feels consistent to the smartphone operating system environment. In the new hand report view, we place the processed hand image at the very top of the screen and anchor it there. Users can refer to the hand image anytime while they are browsing through the hand measurements and analytics. Also, to overcome the small screen size of mobile phones, tap to expand and pinch to zoom features are implemented for the image view. To minimize scrolling, each section of the hand report is divided into different views and they can be switched by tapping the tab bar at the very bottom of the screen. This design also makes extension and modification easier.

![Figure 7. myHand analysis report.](image)

### 3.3 Web-based charting portal and dashboard

Early clinical feedback indicated the need for a Web portal and dashboard that would allow the clinicians and researchers to interpret and manage data from multiple patients, and patients to examine their own information in more depth. The eTreatMD Web Portal was added to extend the functionality of the myHand app to web browsers as shown in Figure 8 and Figure 9. This lets users to access the features of myHand on a wider variety of devices, not limited to smartphones. Mobile platforms are subject to many user interface restrictions, such as limited screen size and the necessity for large hit-boxes on interactive features. The web portal is not subject to these same limitations, and therefore is able to provide the user with a higher level of detail than a mobile application. Through the myHand app, users can evaluate how a single factor affects their pain. Through the web portal, users are able to compare many factors at once.
on a single plot. This added detail allows users and physicians to better evaluate the progression of arthritis in an individual.

Through the eTreatMD Web Portal, users can create new and update existing pain profiles, track their treatments, obtain analysis reports for their hands, and generate graphs to aid in understanding their arthritis. Users and their physicians can use the graphing module to plot pain with respect to a variety of lifestyle factors such as diet, treatments, exercise, and more. These selections can be evaluated both over time, and by category.

Time Plots can graph response over time for pain and any selected category. These graphic representations are particularly useful for comparing things like response to medication or the effects of weather. Category Plots aggregate all pain data within a user defined timeframe corresponding to selected categories and present this data as a bubble chart, where smaller or larger bubbles indicate a more or less occurrences at a particular pain level. These bubble charts are particularly useful for seeing how commonly a diet, activity, or other lifestyle factor affects pain. We provide these two types of charts to provide more effective visual tools to understand and manage the patient journey for those living with arthritis.

![eTreatMD web portal dashboard charting page showing a categorical plot with 5 selections (top) and time based pain graphs.](image)

**Figure 8.** eTreatMD web portal dashboard charting page showing a categorical plot with 5 selections (top) and time based pain graphs.

### 3.4 Current development

Current development is focused on providing enhanced reporting, connectivity to other health platforms, and extension to other types of arthritis, including:

- Providing more statistical details for the data shown in Figures 7 and 8 above, such as correlation factors between pain and selected categories that allows patients to quantify their arthritis response and discover which treatments are most effective.
- Expanding tracking and management features to include foot, knee and hip arthritis, in a full-body arthritis app and expanding smartphone based image measurement and analysis to foot, knee and hip features.
- Developing APIs to connect to existing mobile health management tools, such as Samsung S Health and Apple Health, to automatically input or extract existing dietary, treatment and fitness data between platforms.
- Developing APIs to sync with existing electronic health record systems at clinics and hospitals to transfer eTreatMD reports and health records and to sync with existing video consulting or e-channeling platforms.
4. CONCLUSION

The goal of the work presented in this paper is to provide individuals, who may be developing or have developed arthritis, with a mobile application to assess and monitor the progress of their disease using their smartphone. The mobile application uses image processing including a finger border detection algorithm to monitor the joint thickness and angular deviation abnormalities, which are common symptoms of arthritis. We tested a prototype commercial application with patients in two pilot studies, identified problems with usability and image processing failures and developed and tested algorithm and interface improvements that addressed these problems. We have presented the details of image hand analysis, image quality validation, application-based user guidance, and hand analysis reports through smartphones and web portal dashboards.

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