

Diagnosis of Hypertrophic Cardiomyopathy Using ORB Matching in Python

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ABSTRACT

Hypertrophic cardiomyopathy (HCM) is a cardiovascular disease caused by genetic mutations which results the death young due to cardiac arrest. The person who was diagnosed as HCM will have thickened (hypertrophied) myocardium. Most of the people who have HCM is thickening of the muscle at the lower left chamber of the heart (left ventricle). Two-dimensional echocardiography is an imaging technique which is mostly used to identify left ventricular hypertrophy (LVH). Many researchers suggest to set various criteria to identify the patients with left ventricular hypertrophy (LVH) using cardiogram. This diagnosis outlines the knowledge of the HCM with the help of image matching.

Keywords: Hypertrophic Cardiomyopathy (HCM), Left Ventricular Hypertrophy (LVH), Left intraventricular obstruction (LVOT), Oriented FAST and Rotated BRIEF (ORB), Features from Accelerated Segment Test (FAST), Binary Robust Independent Elementary Features (BRIEF).

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Submitted: 15-10-2020

Revision: 10-11-2020

Accepted Date: 08-12-2020

DOI: 10.31838/jcdr.2020.11.04.55

INTRODUCTION

Nowadays many people were diagnosed as HCM than ever before. After the discovery of its genetic sequences in 1960, it was referred as the most commonly inheritable cardiovascular disease. In Contrary to earlier epidemiologic studies, which estimates a prevalence of 1 in 500 (0.2%) of the general population after the advancement in genetic testing and cardiac magnetic resonance imaging (MRI) raises up to 1 in 200 (0.5%) of all people may be affected.

LEFT INTRAVENTRICULAR HYPERTROPHY (LVH)

An ECG with good specifications is used to detect left ventricular hypertrophy. Since myocardium is thickened it requires considerable high amount of electrical activation to pass through which can be easily identified in the increase in

amplitude of ECG in QRS complex and the raise in ventricular depolarization.

Due to abnormal thickening of the heart muscle, the duration of the QRS complex is widened and electrical activity takes long time to traverse throughout the whole heart which is coined by the term "LVH with QRS widening". Similar effects can be noted in the ST segments or T waves because of repolarization abnormalities known as "LVH with strain" or "LVH with repolarization abnormality". At times, these repolarization abnormalities can mimic ischemic ST changes, and distinguishing between those during a myocardial infarction is important, but often difficult. Deviation of the ST segment in the opposite direction of the QRS complex (discordance), and a typical T wave inversion pattern are typical patterns with LVH.

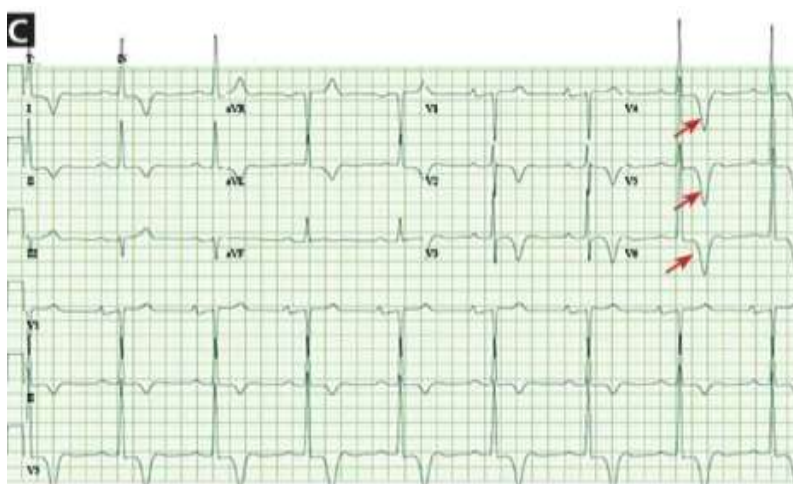


Figure 1: ECG of the patient having Hypertrophic Cardiomyopathy

IMAGE MATCHING

Here we are going to implement various image matching technique in order to compare ECGs in image format. Image matching algorithms are able to produce considerable

amount of accuracy and sensitivity with less demanding computing power compared to their deep learning alternatives on the same dataset. We are using feature extraction techniques to find equivalent ECG readings.

Feature extraction techniques are primarily composed of detecting similar feature key points between images and are then further used to compute translation and rotation. There are various feature detection techniques like SIFT, SURF, ORB, KAZE, and AKAZE.

1. Scale-Invariant Feature Transform (SIFT)

Scale-Invariant Feature Transform (SIFT) is a vision-based feature detection algorithm that detects and describes local key points and features in images. SIFT proposed by Lowe solves the changes in the rotation of the image, affine transformations, intensity, and viewpoint of matching features. This SIFT algorithm has 4 fundamental steps. The first is to estimate the scale of space extrema by extracting local extrema from the DOG pyramid. Secondly, a key point localization where the key point candidates are localized and are further reduced by eliminating images with contrast less than a threshold. The orientation of key points is based on the local image gradient. At the last stage a descriptor generator is used to compute the local image descriptor for each key point based on image gradient magnitude and orientation.

2. Speeded Up Robust Features (SURF)

The Speeded Up Robust Features method (SURF) is a fast and robust algorithm for local, similarity invariant representation and comparison of images. SURF approximates the DoG with box filters. Instead of Gaussian averaging the image similar to SIFT. The squares are used for approximation since the convolution with the square is much faster if the integral image is used. This process can also be parallelized across computers for various scales. SURF employs a BLOB detector based on Hessian-based feature detection to find the points of interest. SURF uses the wavelet responses for orientation assessment, in both horizontal and vertical directions by applying adequate gaussian weights and also for feature detection. In case of feature detection, the neighbourhood around the key point is selected and divided into smaller regions of

interest and then for each smaller region of interest the wavelet responses are taken and represented to get a SURF feature descriptor. The sign of Laplacian which is computed as a part of detection is used for underlying interest points. It is also noted that the sign of Laplacian is inverse for bright blobs on dark background with respect to dark blobs on bright background which is used to distinguish between these two cases. In case of matching the features are compared only if they have the same type of contrast (based on sign) which allows faster matching.

3. Oriented Fast and Rotated Brief (ORB)

The analysis of Electrocardiogram images in order to find that the Patient suffers from Hypertrophic Cardiomyopathy is done by ORB Matching from Open-CV using Python language. ORB is a pre-built algorithm done by Open-CV, an Open Source software used to compare two images of different or the same format using Python on the basis of Pixel patches. FAST stands for Features from Accelerated Segment Test is an open-source feature available in open-cv is used as feature detector in an image it generally looks for the corner of the object with the help of harris corner algorithm it is based on the principle that corner of an object has pixel which may be high intensity or very low intensity when compare to the inner pixels.

First of all, it takes a pixel consider a circle with a radius of 16-pixel blocks and numbers the pixel block which covers the circumference of the circle, take same samples of the pixels and compared its intensity with the intensity at centre of the circle if the majority of it falls in the category it is considered as corners or else it is moves for another pixel.

The Position Vectors of these key points or the circle enclosed at the boundary curve of an object is generated by BRIEF descriptors which are known as Binary Robust Independent Elementary Features. BRIEF descriptors assign binary value vectors the key point found by FAST in the form of a numpy array.

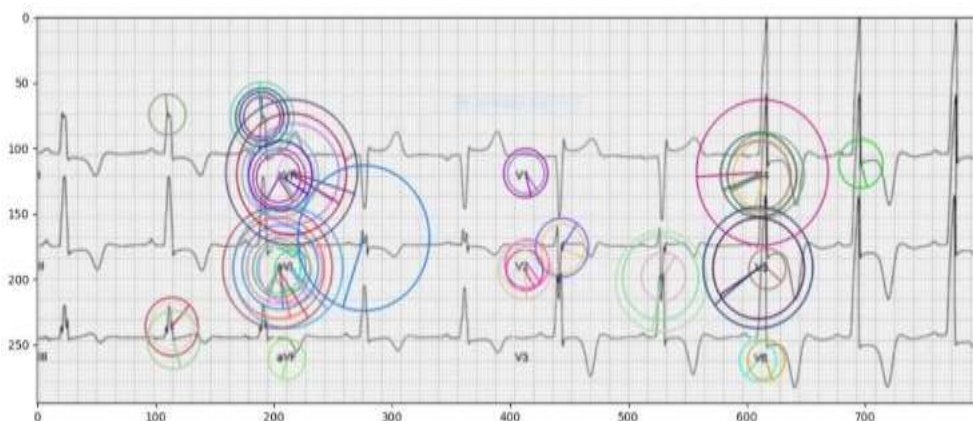


Figure 2: Encircling the region rich of key points

4. Comparison between SIFT, SURF AND ORB Matching

For our Feature detection, we found ORB feature extraction is far more suited to our needs as it is far more robust to rotational and translational variances. In SIFT and SURF, the number of key points detected are always far too high

compared to ORB. The low number of key points detected by ORB Matching is attributed due to the tendency of concentrating key points nearer to the centre of the image. This also makes Orb matching far better performance hence it runs faster among the others.

WORKING OF ORB MATCHER

It calculates the centroid of the highest intensity of the patch resided at the corner. The BRIEF directional vectors provide its dimensions in order to increase the invariance but it performs very poorly when the patch is tilted⁴. It also computes the radius of the patch from the descriptors and chooses its centre for its further calculation by assuming that weighted intensity is located at the centre. The extracted feature and key points are trained with the given algorithm which can represent its weight in the form of a matrix.

Since it FAST is also deployed with BRIEF it gives an additional steer to the patch to get all kinds of possible directional configuration. So that ORB detector can match the patches even if it is rotated.

The position vectors of the identified features in the images were compared using NORM_HAMMING. The matched feature is sorted with respect to the shortest available distance. The matches were stored in the form of lists, the number of matches can be known by the length of the list.

INSTALLATION OF THE MODULE

For plotting the matches in graph, we use matplotlib module plotted in the preference of the shortest distance. In order to access the ORB matcher⁶, we should install open-cv module in python using pip install opencv-python in the command prompt and for plotting the matches use pip install matplotlib command.

WORKING OF THE PROGRAM

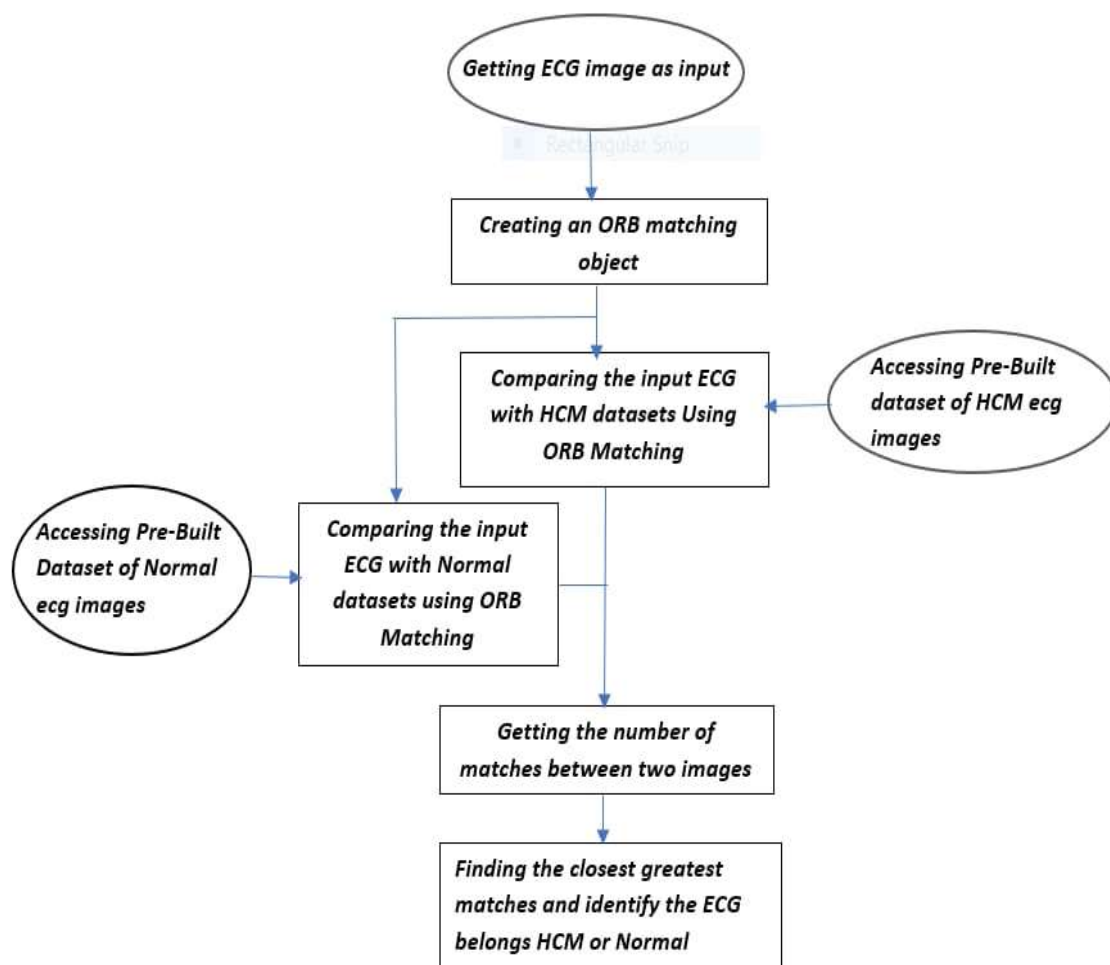


Figure 3: Flow Chart of the Program

The Pre-set data was collected in the form of images for comparison between images. The Patient ECG was accessed by the given path of the image file with the format by cv2.imread attribute. The Patient ECG images were compared with each image in the HCM ECG dataset and a number of matches were appended to the list in a sorted order by Brute Force Matching using orb.detectAndCompute(). Then the Patient ECG image was again compared with each image in the Normal ECG dataset and the number of matches was appended to another list in sorted order. The Patient ECGs were classified on the basis

of which matches are closest depending on the highest number of matches from two different lists.

First the input ECG image is accessed in python by giving its path file with its extension and then using a for loop each path of the dataset images were given. The ORB matcher is initialized and set to compare with each image in the dataset using another loop to get the number of matches. The number of matches was listed separately for normal dataset and HCM dataset; the maximum number of matches with HCM and normal were compared. If the given ECG has the highest matches with HCM then the patient is identified to

have hypertrophic cardiomyopathy or else the patient is normal.

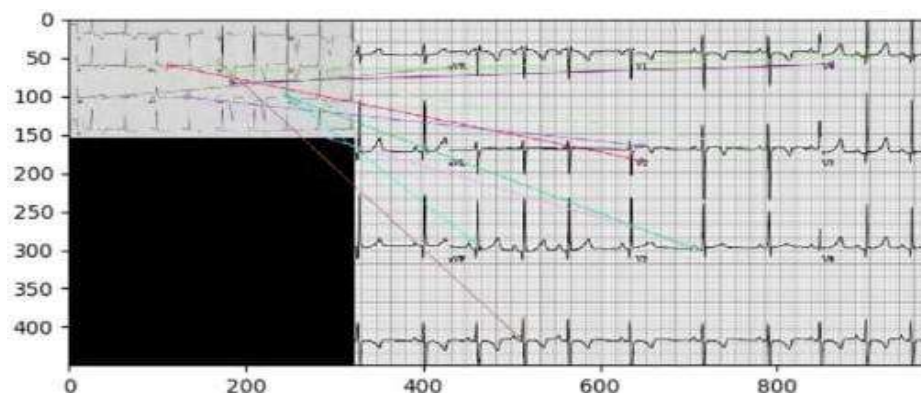


Figure 4: Comparing the HCM ECG with Normal One using ORB Matching

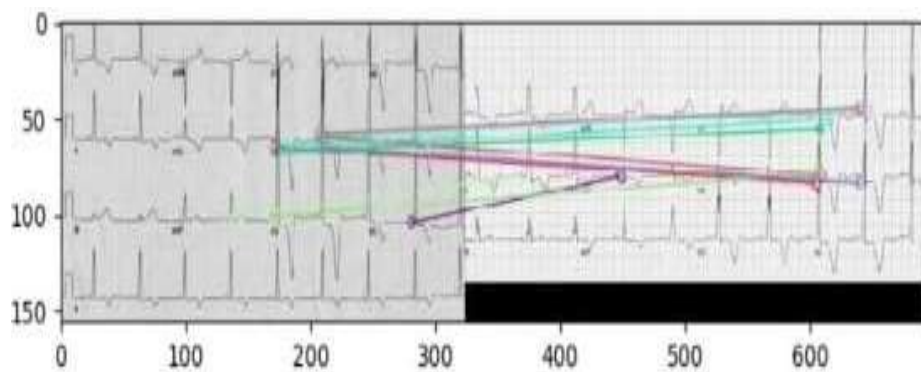


Figure 5: Comparing the HCM ECG with another HCM ECG using ORB Matching

CONCLUSION

This type of identification can be expanded into a live one so that a patient's ECG directly feeds into the system. This feature will help 24×7 monitoring of patients if the cardiologist is unavailable. Whenever they possess HCM it is intimated to the front desk for the treatments. Further expanding the dataset, we are able to predict the HCM precisely and also it is useful for low specialty hospitals to identify them and direct them into recognized hospitals. We are able to convert them into Desktop-based applications to run this procedure.

The goal of this review is to identify the key structural and electrophysiological features underlying the patient's phenotypes with more abnormal ECG. Thus, we are able to detect the presence of Hypertrophic cardiomyopathy in the patient ECG image with the help of machine learning technique using ORB Matching in Python.

CONFLICT OF INTEREST

None

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