expert radiologists in most cases, but there is some research in the field of automatic echocardiography image segmentation by the use of image processing and computer vision methods. Automatic segmentation is desired because it is more accurate and less operator-dependent. It leads to further quantifications such as the measurement of LV volumes, ejection fraction, myocardial volumes, and thickness. It can be also used for evaluating myocardial perfusion by analyzing myocardial intensity changes over time. Due to the intrinsic limitations of echo imaging such as low image intensity, contrast traditional segmentation methods such as edge-based and region-based image processing algorithms could not be accurate enough to overcome the segmentation complexities. Deep learning that is a branch in the computer vision area has been shown to outperform the image processing methods in many tasks.

Objectives: In this study, we used a novel image segmentation neural network (Unet) first introduced in 2014 to segment the myocardium in the left ventricle in 2D four-chamber view echocardiography images.

Methods: The dataset used in this research was the public echocardiography image dataset published in CAMUS (Cardiac Acquisitions for Multi-structure Ultrasound Segmentation) Challenge. The data contained four-chamber view end-systole and end-diastole frames from 450 patients. We used Unet architecture for the segmentation task. Unet is a kind of pyramidal network with encoding and decoding paths. The encoder or contraction path was used to capture the context and features in the image. The second path was the symmetric expanding or decoder path used to enable precise localization. The whole task of the network was to classify each pixel in the image to the background or epicardium classes.

Results: Five-fold cross-validation was used to report the accuracy metrics for the automatic segmentation task. The data were split into the train and test sets several times to evaluate the performance of the neural network. The test and train sets contained 90 and 360 images, respectively. Dice coefficient, Hausdorff distance, and mean absolute distance (MAD) were used to evaluate the accuracy of the method in echocardiography images.

Results: The calculated metrics included a dice coefficient of 90%, Hausdorff distance of 5.01, and MAD of 0.91 for the training set and dice coefficient of 83.14%, Hausdorff distance of 6.55, and MAD of 1.47 for the test set.

Conclusion: We used a novel neural network architecture for the myocardial segmentation task in 2D four-chamber view echocardiography images. We showed that deep learning algorithm automated segmentation can be an accurate alternative to extract the geometric features from images. Using this method can lead the operator to better analyze for LV and myocardial measurements. An approach for future work is expanding the automation to the measurement level from the segmented part.

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Design of Multivariate Hotelling's T^2 Control Chart Based on Medical Images Processing

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Abstract

Background: In the healthcare area of cancer patients, the diagnosis procedure of cancerous tumors and metastases is a valuable and popular research subject in magnetic resonance imaging. A highly accurate diagnosis procedure can be support for doctors in interpreting and diagnosing medical data.

Methods: To address this subject, we used a two-dimensional discrete wavelet transform. First, some features of the image texture were extracted by statistical and transform methods. Then, a genetic algorithm was used for data reduction and feature selection. Afterward, to diagnose bone marrow metastatic patients, we used two methods including a fuzzy c-Means clustering algorithm and a multivariate Hotelling's T2 control chart. In this paper, we employed ADC and T1-weighted images of the pelvic region. From 204 bone marrow samples, 76 features were extracted, six of which were selected and a 204 × 6 feature vector matrix was generated. Finally, the performance of the two proposed methods was compared in terms of diagnosis and accuracy measures.

Results: The results showed that the diagnosis (100%) and accuracy (100%) of the multivariate Ho-

telling's T2 control chart were better than those of the other method, with a diagnosis of 99.49% and accuracy of 99.51%.

Conclusion: In this paper, instead of classification and clustering methods, for the first time, we used a multivariate control chart with the Hotelling's T2 statistic for the diagnosis of patients suspected of bone marrow metastasis. Then, using some patient samples, the performance of this phase I control chart was evaluated, and the results showed the validity of the proposed method. The validation results revealed that the accuracy and specificity metrics were better for the multivariate Hotelling's T2 control chart than for the fuzzy clustering method.

Keywords: Two-Dimensional Discrete Wavelet Transform, Bone Marrow Metastases; Multivariate Hotelling's T2 Control Chart; Fuzzy Clustering; Feature Extraction

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Multi-Institutional Medical Imaging Research Data Collection: Challenges of Standardization of Protocols and Header Information to Make an Imaging Biobank

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Abstract

Background: Iranian brain mapping biobank (IBMB) has three major sources of data to be processed, categorized, and tagged for recurrent use by researchers, including research image acquisition, large scale cohort studies, and routine clinical samples from collaborating institutions. A major limitation of samples coming from routine clinical centers is the potential diversity of data parameters that may prevent to merge databases create biobanks.

Objectives: The study was performed to find out the reliability of a multi-institutional case collection.

Methods: Voluntary case collection was performed from four institutions that signed an agreement with the national brain-mapping laboratory. The centers operated machines from different vendors including Siemens and GE and the scanning protocols were diverse according to the operating technologists. An in-house developed application based on MATLAB 2018b was used to extra DICOM header information from the donated studies. All DICOM headers were imported to a unified database to be analyzed according to the modality, vendor type, and operator protocols.

Results: A total number of 1581 cases were entered into the project with 2414 procedures performed over a six-month period. This collection included 199509 series of images for which all tags were extracted. Except for the modality-specific tags (Table 1), all other tags were found to be uniform regardless of the machine and protocol. The most important tag diversity was seen in the MRI scanning parameters: "Protocol Name", "Scan Options", "Scanning Sequence", "Sequence Name", and "Sequence Variant".

Table 1. List of Modality-specific Tags Unshared Between All Studies

MRI Specific Tags	CT Specific Tags	Radiography Specific Tags
Acquisition Matrix	Convolution kernel	Burned in annotation
Angio Flag	Data collection diameter	Detector activation offset from
dBdt	Distance Source to Detector	Exposure
Echo number	Distance source to patient	Detector active time
Echo time	Exposure	Exposure control mode
Echo train length	Exposure modulation type	Exposure in mAs
Flip angle	Exposure time	Exposure in uAs
Heart rate	Filter type	Exposure time in ms
Imaged nucleus	Focal spot	Exposure time in µs
Imaging frequency	Gantry detector tilt	Field of view shape
In-plane phase encoding direction	Generator power	Focal spot
Inversion time	KVP	Image and fluoroscopy area dose