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An Efficient Augmented Reality for Medical Application based on Peicp-Odcnn Spatial Mapping

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ABSTRACT

Nowadays, augmented reality (AR) is getting popular as AR can provide visual guidance to users in real environment. It is interactive in nature so many medical fields started to prefer it for provoking better performance in diagnosing as well as detecting disease.But it is not that easy to perform due to the challenges it faces for mapping the virtual and real environment.The proposed framework has developed an efficient AR in a medical application for better performance in detecting and diagnosing a disease. The work mainly concentrates to map the virtual 3D medical image on the real object in varied positions without any preregistration or markers. Initially, 2D to 3D conversion is carried out which gives highly qualified image data without any loss. The conversion is then followed with segmentation which segments the 3d medical image region by referring to the environmental data and avoids the horizontal or vertical artifacts using IMR-CNN. To get the rid of relevant features as well as accurate corner point detection and local point detections of the image the work has developed an RJ-FAST BRISK. Finally, based on the features, the spatial mapping is performed by using PEICP-ODCNN, which reduces the error rate caused by varied poses and also reduces the computation time. Experimental results show that the work obtains a mapping accuracy of 92.24% as compared to the existing state-of-the-art method.

Keywords

augmented reality (ar), real environment, improved mask regional convolutional neural network (imr-cnn), Rosenfeld johnson fast binary robust invariant scalable key points (RJ-FAST BRISK), Pose estimation iterative closest point based optimized deep convolutional neural network (PEICP-ODCNN).

Introduction

Augmented Reality (AR) has become more widely used in many different areas, such as education [1], entertainment [2], medicine [3], etc., and it also helps to enhance the view of real-world objects present in the physical environment in terms of virtual elements so that the view is nothing but the blend of real and virtual elements [4]. It is interactive in nature, and hence, it lives between reality and the virtual world. Using AR in the medical application may provide additional features for motion, sizing, colouring, and the effective recognition of diseases [5].Currently, most AR technologies use marker-based AR tracking methods for visual augmentation [6]. It is fast and accurate but, AR markers must be attached to the proper areas of the real objects, and virtual models should be registered for the AR markers in advance. In order to overcome the challenge of AR markers learning based modules has been developed in medical application based on machine learning algorithms, but among these, deep learning is currently the area of interest for researchers in the areas of artificial intelligence [7]. Moreover, the deep learning algorithms make use of a large-scale and hierarchical neural network which provides more efficiency through strong connections [8]. But there is also certain limitation in deep learning models when there is a need of accurate mapping of the virtual and real world environment. In order to conquer the existing

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challenges the work has developed an efficient framework for medical application in the field of AR.

The remainder of the paper is structured as follows: Section 2 reviews and discusses the related works based on AR in medical applications, Section 3 describes the proposed methodology, the experimental analysis of the proposed methodology is performed in section 4, and finally, Section 5 concludes the proposed method.

Literature Survey

Nhu Q. Nguyen *et al.*[9] developed a method to quantify registration accuracy for augmented reality (AR) devices in neurosurgery. The scheme explored the possibility of augmented reality (AR) to improve ease of use for surgical navigation. Although, the existing technologies were extremely accurate, but it had limitation of rough pose alignment.

Francesco Orciuoli*et al.* [10] implemented a mobile app based on Clinical Decision Support System (CDSS). The scheme helped the field operators to measure bedsore, classified its status and made correct decisions about the course of actions, and effectively treated it. The experimentation results showed better results, but the absence of spatial mapping between the virtual and real environment made a huge degradation towards decision making.

Chengrun Li *et al.*[11] developed a printed 3D model that enabled surgeons to see and touch interior structures of the lungs. The augmented reality provided instant guidance to the surgery in the operation room. The technology produced positive values in laparoscopic lung surgery,but the enhancement of printed resolution, cost and time was needed further investigation.

Christina Gsaxner*etal.* [12] implemented an Augmented Reality (AR) system for visualization of medical image data registered with the head or face of the patient prior to intervention. The system was characterized by a slim and easy setup, short training time and acceptance. The result showed the system usability scale score of 74.8 ±15.9, but pre-clinical nature of the scheme was one of its main limitations and further investigation was needed.

Proposed Efficient Framework Based On AR for Medical Application

Augmented Reality in medical applications provokes various beneficial by providing visual guidance to doctors or physicians and supports diagnosis assistance by interpreting visual information into a real environment, but it is quite challenging. The proposed work has developed an efficient AR for medical application as shown in figure 1.

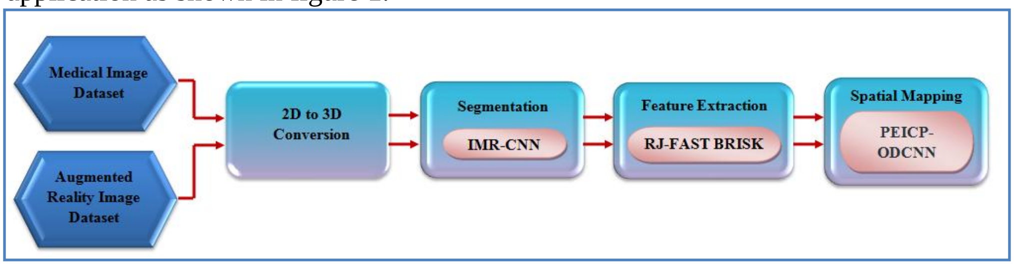

Figure 1: ProposedAR framework for medical application for diagnosing and detecting disease

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2D to 3D construction

The conversion of the 2D to 3D provides with more information and gives better real time world experience than 2D image .The medical scanned image and environment image are captured and converted into 3D by performing depth estimation and depth rendering.

$$\Re_{x,y,z} = \aleph_{CONV}\left(3, \Re^{*}_{x,y}, \Re^{+}_{x,y}\right) \quad \textbf{(1)}$$

Segmentation

It segments the region of interest for the virtual image i.e. the medical scanned image dataset and for the real environment i.e. the physical body. Recently, various methodologies have been carried out but still there remains a challenge such as over segmentation, under segmentation, loss of image data, etc, which leads to an inaccurate AR for medical application. In order to conquer the existing challenges, the work has developed an Improved Mask Regional-Convolutional Neural Network (IMR-CNN).The proposed IMR-CNN for extracted feature map $\Im_F^M = \left\{\Re^*_1, \Re^*_2, \Re^*_3, \Re^*_4, ...\Re^*_N ... \Re^+_1, \Re^+_2, \Re^+_3 \Re^+_4\right\}_{x,y,z}$ consists of following steps:

Step1:RPN is generated, which checks whether the extracted feature map belongs to the real environment objects or not. Thereafter, ROI is evaluated, which eliminates the harsh quantization operation based on feature map by using Trilinear Cubic Interpolation for obtaining more fine-grained information and evaluate Intersection over Union (IOU).

$$\begin{aligned}
\Im_x(\Re^*_n, \Re^+_1) &= \frac{x^* - x^*_0}{x^*_1 - x^*_2}(\Im_{11}) + \frac{x^+ - x^+_0}{x^+_1 - x^+_2}(\Im_{11}) \\
\Im_y(\Re^*_n, \Re^+_1) &= \frac{y^* - y^*_0}{y^*_1 - y^*_2}(\Im_{11}) + \frac{y^+ - y^+_0}{y^+_1 - y^+_2}(\Im_{11}) \\
\Im_z(\Re^*_n, \Re^+_1) &= \frac{z^* - z^*_0}{z^*_1 - z^*_2}(\Im_{11}) + \frac{z^+ - z^+_0}{z^+_1 - z^+_2}(\Im_{11})
\end{aligned} \quad (2)$$

Where, x^*, y^*, z^* represents the coordinates of the virtual image and x^+, y^+, z^+ represents the real environment image. Finally, the bounding box is predicted, now the predicted bounding box is analyzed based on ground truth boxes using IOU. Suppose the predicted bounding box is $\Gamma_p(\Re^*_n, \Re^+_n) = \left(x^p_1, y^p_1, z^p_1, x^p_2, y^p_2, z^p_2\right)$ and the ground truth box is $\Gamma_g(\Re^*_n, \Re^+_n) = \left(x^g_1, y^g_1, z^g_1, x^g_2, y^g_2, z^g_2\right)$ then the IOU is given by

$$\begin{aligned}
\Gamma_p(\Re^*_n, \Re^+_n) &= \left(x^p_2 - x^p_1\right)\left(y^p_2 - y^p_1\right)\left(z^p_2 - z^p_1\right) \\
\Gamma_g(\Re^*_n, \Re^+_n) &= \left(x^g_2 - x^g_1\right)\left(y^g_2 - y^g_1\right)\left(z^g_2 - z^g_1\right)
\end{aligned} \quad (3)$$

Step 2: Masking of the region provides the segmentation mask on each object by analyzing IOU value, and loss value is evaluated for multi-tasking objective function, such as classification loss ($\chi_{cls} = \frac{1}{N_{cls}} \sum \chi'_{cls}\left(\Gamma_g, \Gamma_p\right)$), bounding box location loss ($\chi_b = \Gamma_g - \Gamma_p$), and segmentation loss ($\chi_s = -\frac{1}{m^2} \sum \Gamma_g \log \Gamma_p + (1 - \Gamma_g) \log(1 - \Gamma_p)$). The overall loss function is given by $\Psi_{loss} = \chi_{cls} + \chi_b + \chi_s$.

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Feature Extraction

Feature extraction deals with getting rid of features of the segmented image in order to reduce the computation time as well as the probability of error. The work has developed an RJ-Fast BRISK to extract the necessary or relevant features. The proposed method consists of three important steps:

Step 1: Initially, the original images are half sampled between octaves ($\wp_i$) and intra-octaves ($\wp_i^{'}$") layers. Thereafter, the key points are detected, and in order to obtain a strengthened edge, the work has used RJ that converts the chain coded curve into a connected sequence grid points $\mathrm{T}_{\wp}^{\wp''}(\Re_n^*, \Re_n^+) = (\mathrm{T}_x, \mathrm{T}_y, \mathrm{T}_z)$ and then corner strength are added for each corner points for forward-detection $\Omega_{ai\kappa}^{+} = (x_i - x_{i+\kappa}, y_i - y_{i+\kappa}, z_i - z_{i+\kappa}) = (X_{ik}, Y_{ik}, Z_{ik})$ and backward detection $\Omega_{bi\kappa}^{-} = (x_i - x_{i+\kappa}, y_i - y_{i+\kappa}, z_i - z_{i+\kappa}) = (X_{ik}, Y_{ik}, Z_{ik})$ based on the corner strength($\Omega_{RJ}^{i\kappa}$) which is determined by using:

$$\Omega_{RJ}^{i\kappa} = \frac{(\Omega_{ai\kappa}^{+} . \Omega_{bi\kappa}^{-})}{|\Omega_{ai\kappa}^{+}||\Omega_{bi\kappa}^{-}|} \tag{4}$$

The corner point is selected based upon starting point from $\kappa = \wp_i \ to \ \wp_i^{'}$" that is octave layers and intra octave layers.

Step 2: Key Point Description is performed by adopting a fixed neighbourhood sampling pattern to describe feature points. The feature descriptor (Θ) is generated by using

$$\Theta = \begin{cases} 1 & \Omega(\forall_k^{\theta}, \delta_k) > \Omega(\forall_y^{\theta}, \delta_y) > \Omega(\forall_i^{\theta}, \delta_i) \quad (\forall_i^{\theta}, \forall_y^{\theta}, \forall_k^{\theta}) \in \mathrm{T} \\ 0 & otherwise \end{cases} \tag{5}$$

Step 3: Brisk Descriptor Matching is done based on hamming distance between the virtual image and real image, that is:

$$\hbar(i, j, k) = \sum_{i=1}^{N} \delta_i \oplus \delta_j \oplus \delta_k = \sum_{i=1}^{N} \lambda(\delta_i, \delta_j, \delta_k) \tag{6}$$

The symbol $\oplus$ is the XOR symbol. The value of Hamming distance determines the degree of two BRISK descriptors matching. The greater the value of Hamming distance, the lower the degree of descriptors matching.

Spatial Mapping

Finally, the extracted features of virtual 3D scanned medical image and the real object is mapped using Optimized Pose estimated iterative closest point based optimized deep convolutional neural network (PEICP-ODCNN). The proposed PEICP-ODCNN fixes the real environment as the target and virtual 3D image as a source. In PEICP-ODCNN, based on transformation such as rotation matrix μ and translation vector ν between the source and target point images, the matching is done by minimizing the geometric difference between them. The optimized error function for the transformation matrix is given as:

$$\xi(\mu, \nu) = \frac{1}{N} \sum_{i=1}^{|N|} (m_i - (\mu d_i \mid + \nu)))^2 \tag{7}$$

Where μ and ν represents the matching process between the target dataset that is M^+ $\left(M^+\left(M_i^+ \in m^+\right)\right)$ and the virtual medical image dataset M^* $\left(M^*\left(M_i^* \in d^*\right)\right)$ using the PEICP by minimizing $\xi(\mu,\nu)$. For minimizing the $\xi(\mu,\nu)$, ν and μ must be calculated as,

$$\nu = \frac{1}{|N|}\sum_{i=1}^{|N|}\left(m_i - \mu.\frac{1}{|N|}\sum_{i=1}^{|N|}d_i\right) \tag{8}$$

$$\mu = \lambda\gamma^T \tag{9}$$

Where, λ and γ represents the correlation data between the virtual image and real environment image. Based on the threshold set, the PEICP matches the virtual image with the real environment image. In order to match the virtual image with the varied position of the real environment, the work has been initiated with RMSgradProp-DCNN in ICP. The developed method has to use RMSgradProp optimization to optimize the varied pose to fit with the Virtual image by processing fast and avoids the over fitting problems as well as vanishing gradient problem. Basically, the ICP based Virtual image and real environment image is trained with the deep convolutional neural network and the difference in their alignment is chosen as error rate, therefore, by updating the weights by using RMSgradProp optimization, the virtual image gets accurately match with the real environment image. The error difference between the virtual and real environment images is given by:

$$\forall_{loss} = \sum\left(\zeta_x^+ - \xi_x^*\right)^2 \tag{10}$$

Loss value is optimized by updating the weight (ω_t) by using the old weights (ω_{t-1}) and learning rate (η_t) along with partial differentiation of the loss w.r.t. old weights $\frac{\partial L}{\partial \omega_{t-1}}$ that is:

$$\begin{aligned}
\omega_t &= \omega_{t-1} - \eta_t\left(\frac{\partial L}{\partial \omega_{t-1}}\right)^2 \\
\eta_t &= \frac{\eta}{\sqrt{\alpha_t - e_{avg} + \varepsilon}} \\
\alpha_t &= \sum_{i=1}^{t}\left(\frac{\partial \forall}{\partial \omega_{t-1}}\right) \\
e_{avg} &= \gamma\left(e_{avg\,t-1}\right) + (\gamma - 1)\left(\frac{\partial L}{\partial \omega_{t+1}}\right)
\end{aligned} \tag{11}$$

Where , e_{avg} denotes the weighted average, ε is the positive value which add ups with the denominator to prevent the denominator from becoming zero, η represents the initial learning rate which is assigned as 0.01 and γ is the restriction value which doesn't allow the learning rate to achieve a very big number and α_t denotes the gradient constant . Thus, under optimization, the AR properties are exhibited in the real environment for medical applications.

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Results and Discussion

The proposed framework is validated based on various metrics along with various existing algorithms in order to observe the efficiency of the framework towards augmented reality for medical applications.

Performance analysis of proposed IMR-CNN based on dice coefficients

The proposed framework is analyzed based on the dice coefficient on various noise levels as well as intensity non-uniformity (INU) levels. The proposed IMR-CNN method is analyzed for segmenting the medical scanned image and real-time environmental image. The evaluation of the proposed method is tabulated in table 1.

Table1: Evaluation of proposed IMR-CNN based DC for various noise levels and INU levels

Noise level/INU Level	0%	1%	5%	10%
0%	91.23	91.08	90.89	90.98
20%	92.45	91.45	91.56	91.99
40%	92.56	91.88	91.44	91.78

Table 1 illustrates that the proposed IMR-CNN tends to achieve a better coefficient for different noise levels as well as INU levels. From the table, it can be seen that when the noise level exceeds a certain threshold (i.e., 5% for 0% to 20% of INU and 10% for 20% to 40% of INU), there is a slight decrease in the coefficient value for detecting the borders. But the overall value of the coefficients remains to be above 90%, which is an efficient value for the segmentation process by the proposed IMR-CNN.

Performance analysis of proposed PEICP-ODCNN based on Various Metrics

The analysis elaborates the evaluation based on accuracy, specificity, sensitivity, and precision for the proposed PEICP-ODCNN along with the existing deep convolutional neural network (DCNN), Convolutional Neural Network (CNN), Fast Regional Convolutional Neural Network (Fast-RCNN), Modified Bacterial Foraging Optimization in Convolutional Neural Network (MBFOCNN)). The graphical analysis is illustrated in figure 2.

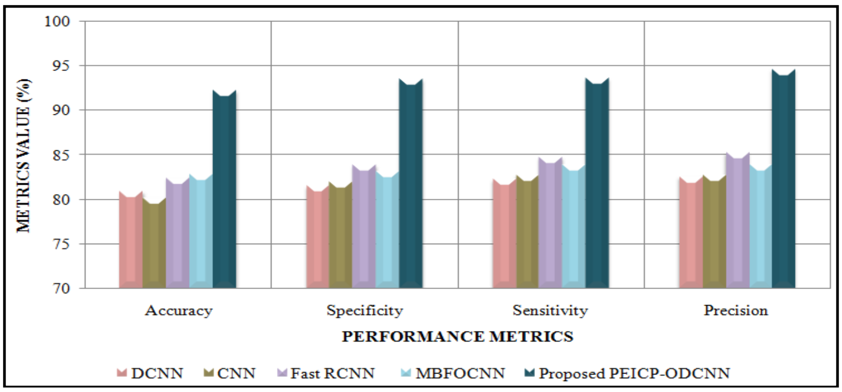

Figure 2: Demonstration of proposed PEICP-ODCNN based on Accuracy, Specificity, Sensitivity and Precision

Figure 2 illustrates the proposed method achieves an accuracy of 92.24%, sensitivity of 93.49%, specificity of 93.63%, and precision of 94.63%, whereas the existing methodology tends to achieve a metrics value ranging between 80.19%-83.88%, which is comparatively less than the proposed method. Thus, the proposed spatial mapping reduces the error rate and obtains a highly qualified AR for medical applications.

Conclusion

The proposed framework enables the efficient utilization of AR in medical application for better performance of detecting and diagnosing adisease. The work mainly concentrates to map the virtual 3D medical image on the real object without any preregistration or markers. The work has carried out IMP-CNN based segmentation of the 3D image in order to focus on the image and curves by using the environment-based data of image. In addition to get rid of feature knowledge the work has developed an RJF-BRISK for extracting relevant features by concentrating more on corner detection. Finally, feature based mapping is done using PEICP-ODCNNwhich allows rough pose estimation and reduces the error as well as computation time. Experimental results have showed that the work obtains an accurate segmentation by achieving a dice coefficient above 90% and also mapping accuracy of 92.24%.

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