Nonlinear Regression Model of a Human Hand Volume: A Nondestructive Method

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Abstract

In this paper, we introduce the new method for volume measurement of objects. A machine vision algorithm is developed which estimates human hand volume from two-dimensional digital images that captured from different views. The proposed algorithm is general and can easily be used for other objects. The novelty of our method lies on the use of ordinary devices, simple algorithm for implementation, and high speed in running program. Main idea includes volume measuring by using projection of object image from different views. Error compensation in object detection and feature extraction performed using suitable estimators such as adaptive neuro fuzzy inference system, Support Vector Regression and new fuzzy weighted support vector regression. This new regressor extremely decreases the errors. Ability of the proposed system is studied in volume measurement of cube and human hand.

Keywords: *Image Processing; Volume Measurement of Human Hand; adaptive neuro fuzzy inference system; Support Vector Regression; Fuzzy weighted Support Vector Regression.*

1. Introduction

Regression models are customarily used to wide range applications and can be categorized from viewpoint of linear and nonlinear models. Regression analysis proceeds from one basic assumption. Specifically, this technique assumes that the relationships between the variables in the analysis are linear. A linear function is simply one of many possible mathematical functions that one might employ to predict one variable using another variable. Perhaps the best reason for describing the relationship between two variables in terms of a linear function is its simplicity. Of course, the most important consideration is simply how well a linear function fits the empirical data [1]. For more consideration, the review of different regression techniques can be followed in several recent books by Gyorfi et al. [2], Hardle [3], [4], and Eubank [5].

We might describe the relationship of two variables in terms of nonlinear function. This method, perhaps, decreases the regression error.

1.1. Nonlinear Regression

A nonlinear regression model can be written as $Y_n = f(x_n, \theta) + Z_n$ where f is the expectation function and x_n is a vector of associated regressor variables or independent variables for the n-th case and Z_n is additive noise. That is, for nonlinear models, at least one of the derivatives of the expectation function with respect to the parameters depends on at least one of the parameters. θ emphasizes the distinction between the linear and nonlinear models. Nonlinear regression are used widely in applications such as predict some measure of software quality [6], estimating parameters of sources in wave field [7]. Some new nonlinear regressors are Adaptive Neuro Fuzzy Inference System (ANFIS) and Support Vector Regression (SVR).

ANFIS was first presented by Jang [8]. It has attained its popularity due to a broad range of useful applications in such diverse areas in recent years as application of MR damper in structural control[9], optimization of fishing predictions [10], vehicular navigation [11], identify the turbine speed dynamics [12], radio frequency power amplifier linearization [13], microwave application [14], image de-noising [15,16], prediction in cleaning with high pressure water [17], sensor calibration [18], fetal electrocardiogram extraction from ECG signal captured from mother [19], identification of normal and glaucomatous eyes from the quantitative assessment of summary data reports of the Stratus optical coherence tomography in Taiwan Chinese population [20], airbag controller design[21], multipurpose sun tracking system[22], fuzzy controller training using ANFIS [23], and intelligent control of a stepping motor drive[24].

Another suitable regressor is Support Vector Regression (SVR). We try developing SVR for increasing robustness against the noise according previous work over support vector machine [25].

1.2. Related Works on Volume Measurement

A volume for non-geometric objects plays the important role in many applications. For example, the left ventricular volume has the utmost importance to determine the efficiency and applicability of diagnostic technique [26]. Other applications of it, are measuring the dimensions of skin wounds [27], and a volume of agricultural product that able us to calculate the mass and density [28,29]. Thus, it is a valuable work to constructing a system for volume measuring. To satisfy all applications, it requires an appropriate method. The variety of volume calculation systems are proposed, but each one is suitable in the limited range of applications. Some of those are including the liquid displacement method [28,29], gas displacement method, stereoscopy and stereo vision [30], resonance frequency [31], 3-D ultrasound image [32,33], photographic tomography using structured light [34,35] and using range sensors [36].

The volume measurement system was explored for a long time. The liquid displacement method is a simple and easy way, but for instance, agricultural products or foodstuffs may be damaged by their immersion into liquid [28]. The gas displacement method too, has its advantages and drawbacks. One of its difficulties is that takes a long time for measurement. Stanley and et. al. [35] measured the surface and area of the human body with structured light that need extra equipment and lead to high computational costs. Schmitt determined the limb volume by using of ultrasound [33]. Determining the volume of objects with this method, require many devices. In this case, they used transducers, amplifiers, transmitter, receiver and signal generator. Cheong and et. al. [26] measured the Tibial Cartilage volume by means of magnetic resonance imaging (MRI) that has its disadvantages. Another method is simulated from human visual system called Stereoscopy [37] that using the image with two different angles for construction 3-D objects.

As mentioned in the above papers some problems exist such as, using extra devices (high technology) and dealing with high computational cost in the process of volume measurement. In this paper, we introduced a novel approach to measuring the volume of human hand based on capturing image of hand from different views. This goal obtains by one cheap digital camera, simple algorithm for implementation, and high speed in running program. For testing the capability and reliability of our method, we apply our system to measure the volumes of cubes, and then we extend the system to measuring the human hand volume. Results for both experiments describe and discuss in the next sections with following organization.

Section 2 appropriates to explain the proposed system including capturing image, preprocessing, feature extraction, and regressor scheme. Experimental results are discussed in section 3. This section pays to describing the method of data collection. Also, results of each part of the proposed system are checked and obtained errors are studied. Finally, conclusion and future works are presented in section 4.

2. The Proposed System

Our method is similar to the stereoscopy and stereo vision with some differences. We capture objects from variety of views only with one digital camera, in contrast to using camera arrays. Furthermore, we don't involve in obtaining 3-Dimensional models because of its complexity. The volume measurement flow chart is shown in the Fig. 1.

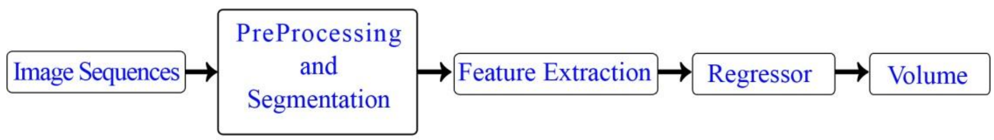

Fig. 1: The proposed System

Image sequences are images that captured from different views of same object as shown in Fig 3 and 7.

These views (orientations) must be the same for all different objects. Wide changes in these views affect the system performance. Besides, these views must reflect all features of object such as eminence and notch. For example, suppose there are two similar cubes that in one of them exists a hole. So capturing operation must contain the effect of hole in the measurement of cube volume. Otherwise, the system shows the same volume for two cubes. Of course, we try to lessen the number of captured images to boost the system speed. Nonetheless, it is a trade-off between precise and speed.

In the pre-processing and segmentation section, thresholding, and region labeling are accomplished. Segmentation is one of the important tools in image processing. Various algorithms have been proposed that we can find them in image processing books [38-42]. In this paper, we use segmentation algorithm based on fuzzy c-means algorithm which is a clustering technique. This algorithm is explained in the Appendix part a. After segmentation, object is extracted using labeling and number of pixels is applied to regressor as feature. The extracted features from images depend on the shape of objects. Then, a regressor calculates the volume of objects. This regressor approximates the function *f* that has the following form:

$$V = f\left(x_1,\dots, x_n\right) \tag{1}$$

Where $x_1,\dots,x_n$ are number of pixels from different views of object. V is the volume of object in cubic centimeters. The *f* is a function that approximates the object volume from the input data. As a function, *f* is highly non-linear, but it may be approximated with some regression methods such as ANN[1], ANFIS[2], SVR[3] and FWSVR[4]. Despite of some methods

[1] Artificial Neural Network

such as that used in [28], our function need not any proportional constant and straightly calculates the volume. Due to this subject, our method is speedier in running. To achieve the best results, we approximate this function with three methods: adaptive neuro fuzzy inference system, Support Vector Regression and the proposed Fuzzy Weighted support vector regression. In following subsections, we describe these methods.

2.1. Adaptive neuro Fuzzy Inference System

Recently, there has been a growing interest in combining neural network and fuzzy inference system. As a result, neuro-fuzzy computing techniques have been evolved. Neuro-fuzzy systems are fuzzy systems which use neural networks theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy integrates to synthesize the merits of both neural networks and fuzzy systems in a complementary way to overcome their disadvantages.

ANFIS has been proved to have significant results in modeling nonlinear functions. In an ANFIS, the membership functions (MFs) are extracted from a data set that describes the system behavior. The ANFIS learns features in the data set and adjusts the system parameters according to given error criterion. In a fused architecture, NN learning algorithms are used to determine the parameters of fuzzy inference system. Below, we have summarized the advantages of the ANFIS technique.

- Real-time processing of instantaneous system input and output data's. This property helps using this technique for many operational researches problems.
- Offline adaptation instead of online system-error minimization, thus easier to manage and no iterative algorithms are involved.
- System performance is not limited by the order of the function since it is not represented in polynomial format.
- Fast learning time.
- System performance tuning is flexible as the number of membership functions and training epochs can be altered easily.
- The simple if–then rules declaration and the ANFIS structure are easy to understand and implement.

2.2. Support vector regression

The support vector regression (SVR) is a supervised learning method that generates input-output mapping functions from a set of labeled training data. The mapping function can be either a classification function, i.e., the category of the input data, or a regression function. Initially developed for solving classification problems, support vector techniques can be successfully applied to regression.

Suppose we are given training data $\{(X_1,Y_1),(X_2,Y_2),...,(X_n,Y_n)\}\subset X\times R$, where X denotes the space of the input patterns (e.g. $X=R^D$). In ε-SV regression [43], our goal is to find a function f(x) that has at most ε deviation from the actually obtained targets y_i for all the training data. The regressor must not only fit the given data well, but also make minimal errors in predicting the values at any other arbitrary point in R^D. Nonlinear regression is

[2] Adaptive Neuro Fuzzy Inference System
[3] Support Vector Regression
[4] Fuzzy Weighted Support Vector Regression

accomplished by fitting a linear regressor in a higher dimensional feature space. A nonlinear transformation Φ is used to transform data points from the input space (with dimension D) into a feature space having a higher dimension L $L > D$. The nonlinear mapping is denoted by $\Phi : R^D \rightarrow R^L$.

This problem can be written as a convex optimization problem; hence, we arrive at the formulation stated in [43].

$$Min \ \ \frac{1}{2}\|W\|^2 + C\left(\sum_{i=1}^{l}(\xi_i + \xi_i^*)\right)$$

$$\begin{aligned} s.t. \quad & y_i - W^T\phi(X_i) - b \le \varepsilon + \xi_i \\ & -y_i + W^T\phi(X_i) + b \le \varepsilon + \xi_i^* \\ & \xi_i, \xi_i^* \ge 0 \end{aligned} \tag{2}$$

Where C > 0 is a constant, ξ_i, ξ_i^* are slack variables for soft margin SVM, which allow accepting some deviation larger than ε that is precision. It turns out that in most cases the optimization problem (2) can be solved more easily in its dual formulation.

$$\begin{aligned} & Max \ \ -\frac{1}{2}\sum_{i,j=1}^{l}\left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right)K\left(X_i, X_j\right) - \\ & \varepsilon\sum_{i=1}^{l}\left(\alpha_i + \alpha_i^*\right) + \sum_{i=1}^{l} y_i\left(\alpha_i - \alpha_i^*\right) \\ & s.t \qquad \sum_{i=1}^{l}\left(\alpha_i - \alpha_i^*\right) = 0 \quad , \ \alpha_i, \alpha_i^* \in [0, C] \end{aligned} \tag{3}$$

Where α_i, α_i^* are Lagrange coefficients and matrix K is termed as a kernel matrix and its elements are given by

$$K\left(X_i, X_j\right) = \phi(X_i)^T\phi\left(X_j\right) \ , \quad i, j = 1,2,...M \ .$$

By solving (3) we can find Lagrange coefficients and by replacing them, we have

$W = \sum_{i=1}^{l}\left(\alpha_i - \alpha_i^*\right)\times\phi(X_i)$, thus

$$f(x) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)K\left(X_i, X_j\right) + b \tag{4}$$

2.3. Fuzzy Weighted Support Vector Regression

In the newer approach, the concept of the TSK fuzzy modeling approach [44] is adopted. Unlike conventional modeling approaches, where a single model is used to describe the global behavior of a system, the TSK modeling is essentially a multi model approach in which simple sub models are combined to describe the global behavior of the system. The concept of the TSK fuzzy models is simply discussed as follows. Generally, a TSK fuzzy model consists of a set of if-then rules with the form

$$\begin{aligned}&R^i : If \;\; x^1 \; is \; A_1^i \; and \; x^2 \; is \; A_2^i \; and \ldots x^q \; is \; A_q^i \; then \\ &h^i = f_i(\vec{x};\vec{a}^i) = a_o^i + a_1^i x^1 + \ldots + a_q^i x^q\end{aligned} \tag{5}$$

for $i = 1,2,\ldots,c$, where C denotes the number of rules, A_j^i is the corresponding fuzzy set (i.e. membership function), and $\vec{a}^i = (a_o^i, a_1^i, \ldots, a_q^i)$ is the parameter set in the consequent part. The predicted output of the fuzzy model is inferred as

$$\hat{y} = \frac{\sum_{i=1}^{c} w^i h^i}{\sum_{i=1}^{c} w^i} \tag{6}$$

where $h^i = f_i(\vec{x};\vec{a}^i) = a_o^i + a_1^i x^1 + \ldots + a_q^i x^q$, are the output of the rule R^i and the weight w^i is obtained by $A_j^i(\vec{x}_k)$. Both the parameters in the premise parts and the consequent parts for the TSK fuzzy model are required to be identified. Besides, the number of rules is also specified.

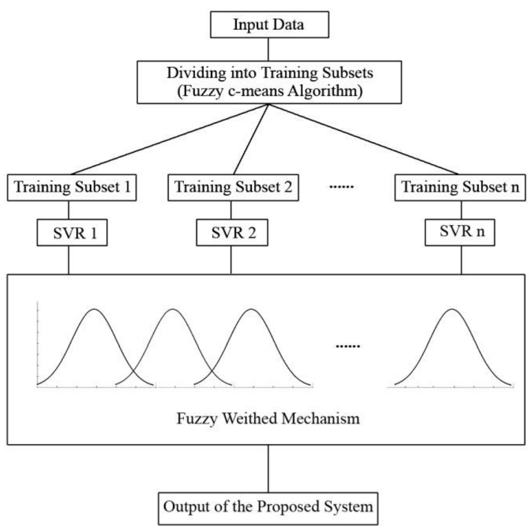

Fig2. Procedure of the Proposed Method

The difference between our FWSVR and [11] is in the adaption of Fuzzy Weighted Mechanism. We adapt Gaussian membership functions, instead of triangle membership functions. Also the fuzzy weighted mechanism is constructed by using the centers and the spread width generated in the FCM clustering algorithm. It is worth noting that the proposed approach is different from the SVM-based fuzzy basis function inference system [45].

In the next subsection, we explain the process of measuring the volume for two objects: cube and human hand.

2.4. Cube Volume Measurement

We know that volume of cube obtain from formula $V = a \times b \times c$, where a, b and c are the cube sides. If all cubes (of different volumes) are photographed in exactly same orientations, then the cube volumes would be a monotonic function of the areas extracted from images.

The black color of all cubes in white background helps the segmentation algorithm to work better. To eliminate the object shadows, we use three lights from three different points. Capturing conditions for all cubes must be the same. These conditions are such as distance from camera, capturing orientation and number of images for each cube. We capture them from four different views:

i. With respect to greater face
ii. With respect to middle face
iii. With respect to smaller face
iv. With respect to one fixed corner

These four images are shown in fig. 3:

(1) (2) (3) (4)

Fig. 3: A Cube from Different Views

Then pre-processing and segmentation are applied to the fig .3. Resultant image showed in fig. 4.

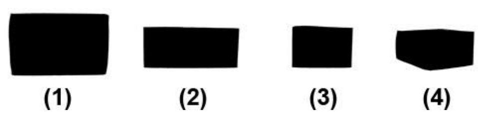

Fig. 4: Cube Images After Segmentation

Our scrutiny on the errors with and without image number 4 in fig. 3 shows that this view is not very effective and the results are the same as state which this view doesn't exist.

The features extracted from these images are areas measured for every view. These features are same as x_1 to x_4 in equation (1). Proportion of real volume and measured volume using the proposed approach must be equal approximately, for all cubes. However, due to errors in making cubes, this ratio varies for each cube. Fig 5 depicts these variations.

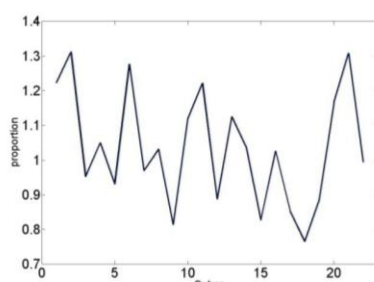

Fig. 5: Proportion of Real Volume and Measured Volume Using the Proposed System

2.5. Human Hand Volume Measurement

After cubes, we apply the proposed system to measure of human hand volume. For obtaining learning data, the volume of human hand is measured using variation of water volume as shown in Fig 6. To lessen the errors in this stage, we measure ten times every hand volume and calculate its average for learning regressor.

Fig. 6: Measuring Hand Volume for Regressor Training

Due to variety in color of different hands, every person wears white glue. To capture the images of hand, we define seven points of view as shown in Fig. 7.

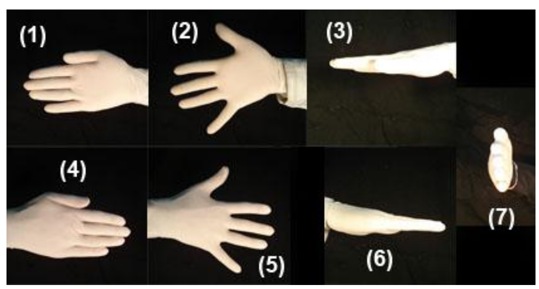

Fig. 7: Hand from Different Views

The grayscale images are obtained after applying pre-processing and segmentation procedure. Fig 8 shows results.

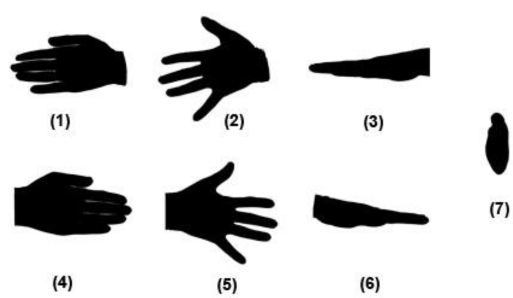

Fig. 8: Hand Images After Pre-processing

In this case, areas of hand, in each image are the inputs of function in equation (1) (e.g. x_1 to x_7). The images 2 and 5 are similar to images 1 and 4 but with different boundary. So it is better that they do not eliminate.

3. Experimental Results

Two experiments over volume measuring of cube and human hand are performed to check the idea. 22 cubes are constructed and four different views are selected for capturing them. Also for measuring of hand volume, 11 human with different hand volumes are selected. 77 images from 7 views are collected.

Different errors occur in these experiments as,

- ✓ Errors in constructing cubes
- ✓ Errors in segmentation of human hand and cubes
- ✓ Errors in water displacement method
- ✓ Little number of training samples.

These errors influence the obtained results. The classifiers are trained with the *leave-one-out* method. Obtained errors is different between main volumes (it is measured for hand according to Fig 6 and for cubes with a geometrical relation) and obtained volume from trained classifiers. Fig 9, 10 and 11 show errors for cubes in ANFIS, SVR and FWSVR respectively.

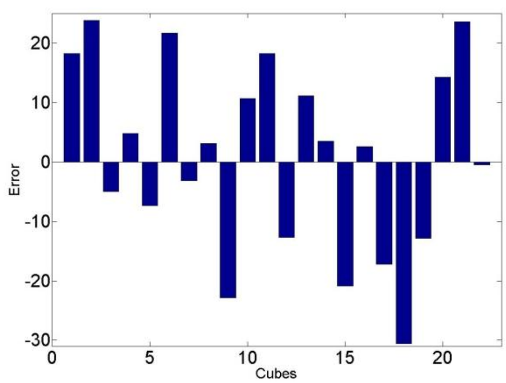

Fig. 9: Error of ANFIS for Cubes

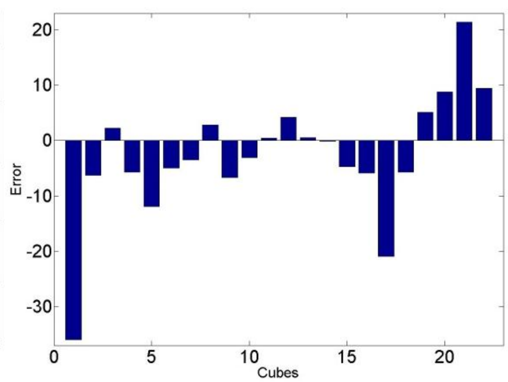

Fig. 10: Error of SVR for Cubes

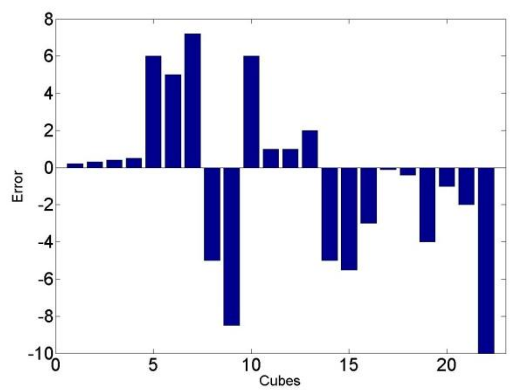

Fig. 11: Error of FWSVR for Cubes

The best applied kernel for SVR (FWSVR) is obtained by RBF kernel with variance σ^2 equals to 4 according as follows,

$$K(x,y) = \exp\left(-\frac{\|x-y\|}{2\sigma^2}\right) \tag{6}$$

σ^2 must increase for small number of training samples however error increase in testing procedure.

Similar work performs over measuring of hand volume. Fig 12, 13 and 14 show errors over test samples.

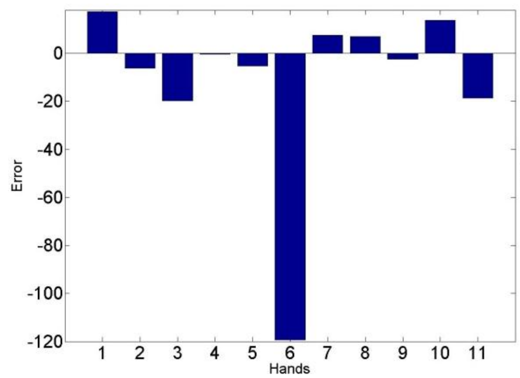

Fig. 12: Error of ANFIS for Human Hand

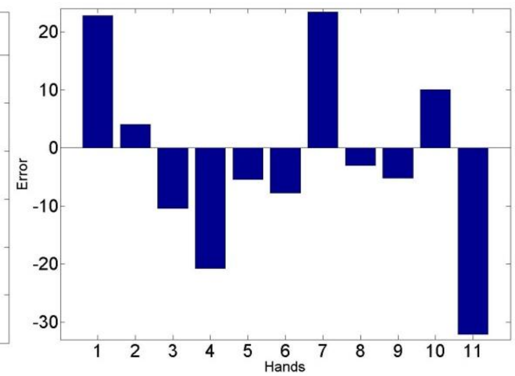

Fig. 13: Error of SVR for Human Hand

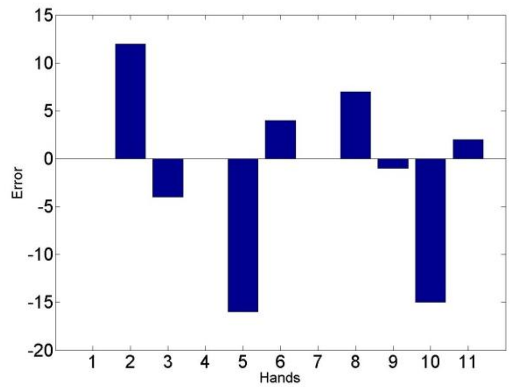

Fig. 14: Error of FWSVR for Human Hand

In the table 1 the average error of different classifiers are summarized:

Table 1: Average Errors

	ANFIS	SVR	FWSVR
Cube	13%	7.45%	3.36%
Hand	21.27 %	12.45 %	5.54%

We can conclude that the FWSVR has the best performance amongst the other classifiers. Furthermore, the effect of sample shortage for training the classifier is obvious.

4. Conclusion and Future Work

An algorithm, which estimates the volume of geometric and non-geometric objects, has been developed. The algorithm is based on the number of pixels of object from different views. Because of the proposed scheme is not based on the geometrical features (length, width, height and so on), it should be able to applied into different objects. The regressor can be retrained to obtain volume of almost every object.

For achieving better results with lower error, we will contrive to improve the environment illumination and camera parameters. We intend to extend our database for hand volume measurement. With greater database, the regressor will lead to better results. In addition, with finding better features of objects, as boundary and so on, we will enhance regression. As mentioned the capturing orientation is very important and we will search for better and more reliable capturing orientations. Also, we intend to apply our method to measuring the human body volume.

Appendix

Fuzzy c-means algorithm

One of the most widely used fuzzy clustering models is fuzzy c-means (FCM). The FCM algorithm assigns memberships to which are inversely related to the relative distance of to the point prototypes that are cluster centers in the FCM model. Some problems in FCM are as follows,

a) Samples with equidistance to centers

b) Measurement of distance to crisp centers

c) Data's are crisp

Objective function in FCM is

$$J_m(U,V) = \sum_{k=1}^{n}\sum_{i=1}^{c} u_{ik}^{m} \left\| x_k - v_i \right\|^p \tag{a-1}$$

Where $V = \{v_i, i = 1,2,..., c\}, U = \{u_{ik}^m\}$ are centers and membership functions and $X = \{x_1,...x_n\} \subset R^S$ are data's. $v_i \in R^s$ is center of i_{th} centers. $u_{ik} \in [0,1]$ is membership of i_{th} data to k_{th} centers. N samples are clustered to c cluster as following constraints are satisfied.

$$M_{fcm} = \left\{ U \in R^{c*n} \left| \begin{array}{l} \forall i,k : \circ \le u_{i,k} \le 1 \ ; \\ \sum_{i=1}^{c} u_{ik} = 1 \ , \sum_{k=1}^{n} u_{ik} > 0 \end{array} \right. \right\} \tag{a-2}$$

Optimization procedure gives,

$$v_i = \frac{\sum_{k=1}^{n} (u_{i,k})^m x_k}{\sum_{k=1}^{n} (u_{i,k})^m} \tag{a-3}$$

$$u_{ik} = \sum_{l=1}^{c} \left(\frac{\|Y_k - v_i\|}{\|Y_k - v_l\|} \right)^{-2/(m-1)} . \tag{a-4}$$

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