Comparative Analysis of Interpolation Methods for Bilateral Asymmetry

Jelena Bozek, Mislav Grgic, Kresimir Delac
University of Zagreb, Faculty of Electrical Engineering and Computing
Department of Wireless Communications
Unska 3/XII, HR-10000 Zagreb, Croatia
E-mail: *jelena.bozek@fer.hr*

***Abstract* - First step in bilateral asymmetry detection in mammographic image analysis is alignment of the left and right breast. Alignment may help radiologists in their search for signs of bilateral asymmetry as well as in comparison of corresponding regions in breasts with a computer aided detection system. Different interpolation methods may be used for breast alignment. We have compared nearest neighbor interpolation, bilinear interpolation, B-spline interpolation, cubic interpolation, cubic Schaum interpolation and o-Moms interpolation and their impact on mammographic images. We evaluated interpolation quality using mathematical similarity measures such as normalized 2-D cross-correlation coefficient, peak signal to noise ratio (PSNR) and structural similarity measure (SSIM). Normalized 2-D cross-correlation coefficient and SSIM have shown best results for B-spline interpolation while PSNR measure has shown best results for nearest neighbor interpolation. According to all three used measures the worst interpolation quality has cubic interpolation with kernel size of 8 x 8.**

Keywords - mammographic images; bilateral asymmetry; interpolation methods; breast alignment

I. INTRODUCTION

Breast cancer is the most common cancer in women. To date, one of the best noninvasive examination procedures is mammography. Mammography enables early detection and diagnosis of breast cancer which increases survival rate. One of the breast abnormalities that may indicate cancer or its future development is bilateral asymmetry, i.e. asymmetry of breast tissue between corresponding regions in left and right breast. Asymmetric breast tissue occurs in approximately 3% of the population [1]. According to the American College of Radiology Breast Imaging Reporting and Data System [2] there are two types of bilateral asymmetry: global asymmetry and focal asymmetry. Global asymmetry is defined when a greater volume of fibroglandular tissue is present in one breast compared to the corresponding area in the other breast and focal asymmetry is circumscribed area of asymmetry seen on two views, but it lacks the borders and conspicuity of a mass. Focal asymmetry is usually an island of healthy fibroglandular tissue that is superimposed with surrounding fatty tissue.

In order to enable comparison of corresponding regions in left and right breast, some researchers propose some kind of registration or alignment of the breasts [3-7]. However, the alignment procedure is a challenging task due to the natural asymmetry of the breasts, absence of good corresponding points between left and right breast images to perform matching and distortions inherent to breast imaging [8]. Thus, some researchers propose methods where registration and alignment of the breasts is not necessary [9-12].

Most alignment procedures use some breast landmarks to perform matching such as nipple, pectoral muscle and points on the breast border [3-7]. In our previous work we have used two points on the breast border to perform alignment [13]. First point was defined as the furthest point on the breast contour in horizontal direction and the second point was defined as the furthest point on the breast contour in the vertical direction as it is depicted in Fig. 1.

Depending on the application, different interpolation methods give different results. Lehman et al. [14] have made an overview of interpolation methods in medical imaging with the application of correction of the aspect ratios in CCD-photographs of a human eye, rotation of head MRI sections and prospective projections of chest X-ray images. In their later work [15] they expanded their analysis with B-spline interpolation techniques of different degrees.

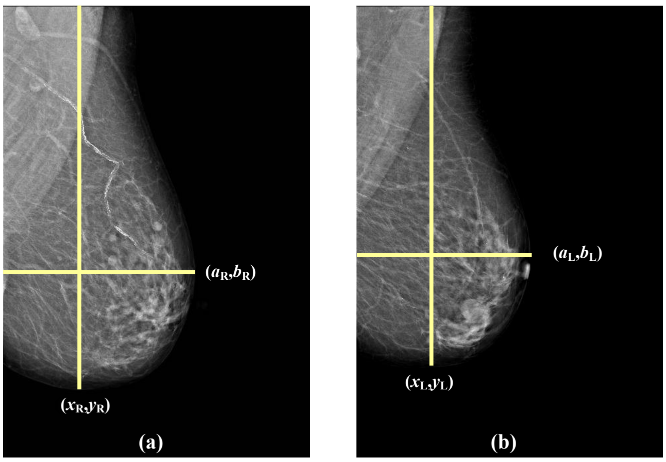

Figure 1. Coordinates of the furthest points on the breast contour in the: (a) flipped right image, (b) left image

Georgsson [7] evaluated impact of nearest neighbor, linear and cubic interpolations when used for the breast alignment. He used the measures of connectivity and concluded that the nearest neighbor has the best connectivity properties.

This paper presents and evaluates different interpolation methods and their impact on mammographic images with bilateral asymmetry. Evaluated interpolation methods are presented in Section 2. Obtained results are presented and discussed in Section 3. Conclusions are given in Section 4.

II. INTERPOLATION METHODS

Traditional interpolation can be expressed as:

$$f(\mathbf{x}) = \sum_{k \in Z^q} f_k \cdot \varphi_{\text{int}}(\mathbf{x} - \mathbf{k}) \tag{1}$$

$$\forall \mathbf{x} = (x_1, x_2, ..., x_q) \in R^q$$

$$\forall \mathbf{k} = (k_1, k_2, ..., k_q) \in Z^q$$

where interpolated value $f(x)$ at some (perhaps noninteger) coordinate x in a space of dimension q (q = 2 for images) is calculated as a linear combination of samples f_k evaluated at integer coordinates k and interpolation sample weights $\varphi_{\text{int}}(x\text{-}k)$ [16].

As an alternative approach, the generalized interpolation can be considered as the form:

$$f(\mathbf{x}) = \sum_{k \in Z^q} c_k \cdot \varphi(\mathbf{x} - \mathbf{k}) \quad \forall \mathbf{x} \in R^q \tag{2}$$

The main difference between the equations (1) and (2) is the introduction of coefficients c_k in place of the sample values f_k [16]. It enables new ways of computation, because the interpolation can now be counted in two steps: (1) determination of the coefficients c_k from the known samples f_k, and (2) determination of the interpolation values $f(x)$ from the calculated coefficients. Two step computation allows selection between more basis functions φ_{int}, in relation to the case when it was $c_k = f_k$. Lack of this approach is greater execution time, but it is compensated with larger selection of basis functions and quality of final interpolation.

A. Nearest Neighbor Interpolation

Nearest neighbor interpolation has the simplest basis function. As a result it provides a constant - repeated input pattern. The basis function can be expressed as:

$$\varphi^0(x) = \begin{cases} 0, & x < -1/2 \\ 1, & -1/2 \le x < 1/2 \\ 0, & x \ge 1/2 \end{cases} \tag{3}$$

The main advantage of this interpolation is its simplicity. For any coordinate x for which we calculate the interpolated function f(x) there is only one sample f_k that contributes, independently on the number of dimensions q. However, this will result in low-quality of the final image. The advantage of this procedure is that the whole interpolation process is completely reversible and there is no loss of the initial data in the final image.

B. Linear Interpolation

Linear interpolation functions are often used due to their low complexity. They are only slightly more complex than the nearest neighbor method. In one dimensional space two points are necessary to calculate the interpolated value. In two dimensional spaces linear interpolation is called bilinear and four surrounding points are necessary for calculating interpolated value. Its kernel in one dimension can be described as:

$$\beta^1(x) = \begin{cases} 1 - |x|, & |x| < 1 \\ 0, & |x| \ge 1 \end{cases} \tag{4}$$

C. B-Spline Interpolation

Generally, B-spline functions are denoted as β^n, where $n \in$ N presents the function level. The functions are expressed by:

$$\beta^n(x) = \sum_{k=0}^{n+1} \frac{(-1)^k \cdot (n+1)}{(n+1-k)! \cdot k!} \cdot \left(\frac{n+1}{2} + x - k\right)_+^n \tag{5}$$

$\forall x \in R, \forall n \in N$ where $(x)_+^n = (\max(0, x))^n$.

Important characteristic of B-spline functions is that β^n functions can be computed recursively by:

$$\frac{d}{dx}\beta^n(x) = \beta^{n-1}\left(x + \frac{1}{2}\right) + \beta^{n-1}\left(x - \frac{1}{2}\right), \ n > 0 \tag{6}$$

Another important characteristic is computing the exact gradient of a signal given by a discrete sequence of interpolation coefficients c_k using the following form:

$$\frac{d}{dx} f(x) = \sum_{k \in Z} c_k \cdot \frac{d}{dx} \cdot \beta^n(x-k) = \sum_{k \in Z} (c_k - c_{k-1}) \cdot \beta^{n-1}\left(x - k + \frac{1}{2}\right) \tag{7}$$

where the n-times continuous differentiability of B-splines ensures that the resulting function is smooth when $n \ge 3$, continuous when $n \ge 2$ and bounded when $n \ge 1$ [16].

Now we can consider some special cases for n.

For degree $n = 0$ (β^0) we have approximately the same case as the nearest neighbor method. The difference can be seen in some exceptional cases (evaluation at half-integers) when interpolation with β^0 requires the computation of the average between two samples.

For degree $n = 1$ the B-spline function does not differ from the linear interpolation.

For degrees $n > 1$ the B-spline function does not have the characteristic of being an interpolation function. This means that the expression (1) must not be used. After computing interpolation coefficients the expression (2) may be applied.

Commonly used B-spline function is cubic B-spline ($n = 3$) which is expressed as follows:

$$\beta^3(x) = \begin{cases} \frac{2}{3} - |x|^2 + \frac{|x|^3}{2}, & 0 \le |x| < 1 \\ \frac{(2-|x|)^3}{6}, & 1 \le |x| < 2 \\ 0, & 2 \le |x| \end{cases} \quad (8)$$

As mentioned, this basis function is not an interpolation function. Thus, digital filtering is applied in order to determine coefficients so that the function goes through the data points exactly [17].

D. Cubic Interpolation

General expression for cubic four-point interpolation is as follows:

$$h_4(x) = \begin{cases} (a+2)|x|^3 - (a+3)|x|^2 + 1, & 0 \le |x| < 1 \\ a|x|^3 - 5a|x|^2 + 8a|x| - 4a, & 1 \le |x| < 2 \\ 0, & 2 \le |x| \end{cases} \quad (9)$$

Factor *a* can take different values (-1/2, -3/4, -1, -1.3). For *a* = -1/2 results of interpolation should be optimal [18].

Six-point and eight-point interpolation kernels are expressed in (10) and (11):

$$h_6(x) = \begin{cases} (6/5)|x|^3 - (11/5)|x|^2 + 1, & 0 \le |x| < 1 \\ -(3/5)|x|^3 + (16/5)|x|^2 - (27/5)|x| + 14/5, & 1 \le |x| < 2 \\ (1/5)|x|^3 - (8/5)|x|^2 + (21/5)|x| - 18/5, & 2 \le |x| < 3 \\ 0, & 3 \le |x| \end{cases} \quad (10)$$

$$h_8(x) = \begin{cases} (67/56)|x|^3 - (123/56)|x|^2 + 1, & 0 \le |x| < 1 \\ -(33/56)|x|^3 + (177/56)|x|^2 - (75/14)|x| + 39/14, & 1 \le |x| < 2 \\ (9/56)|x|^3 - (75/56)|x|^2 + (51/14)|x| - 45/14, & 2 \le |x| < 3 \\ -(3/56)|x|^3 + (33/56)|x|^2 - (15/7)|x| + 18/7, & 3 \le |x| < 4 \\ 0, & 4 \le |x| \end{cases} \quad (11)$$

E. O-Moms Interpolation

Moms functions (*Maximal Order of Minimal Support*) are more general functions than the B-spline functions. They are denoted with index *n* which represents degree of the function. B-splines are those Moms functions that are maximally differentiable. There are several other classes in this family of functions, in particular, the o-Moms functions (optimal-Moms). O-Moms functions have minimal least-squares approximation constant [16].

Moms functions can be expressed using the B-spline functions as follows:

$$Moms^n(x) = \beta^n(x) + \sum_{m=1}^{n} c_m \cdot \frac{d^m}{dx^m}\beta^n(x) \quad (12)$$

Third degree o-Moms function is expressed as follows:

$$o-Moms^3(x) = \beta^n(x) + \frac{1}{42} \cdot \frac{d^2}{dx^2}\beta^3(x)$$
$$= \begin{cases} \frac{1}{2}|x|^3 - |x|^2 + \frac{1}{14}|x| + \frac{13}{21}, & 0 \le |x| < 1 \\ -\frac{1}{6}|x|^3 + |x|^2 - \frac{85}{42}|x| + \frac{29}{21}, & 1 \le |x| < 2 \\ 0, & 2 \le |x| \end{cases} \quad (13)$$

Like B-splines, O-Moms are also not interpolating functions. Fortunately, the digital filter similar to the one used for B-spline interpolation may be applied.

F. Schaum Interpolation

Schaum functions are a class of Moms functions and can be represented as a weighted sum of B-splines and of their even-order derivatives. They have same order and same support as B-splines and o-Moms [16]. Their main difference compared to B-spline and o-Moms functions is that they are interpolating so they do not need filtering. Cubic Schaum function expressed using third degree B-spline function is:

$$sch^3(x) = \beta^3(x) - \frac{1}{6}\frac{d^2}{dx^2}\beta^3(x)$$
$$= \begin{cases} \frac{1}{2}|x|^3 - |x|^2 - \frac{1}{2}|x| + 1, & 0 \le |x| < 1 \\ \frac{1}{6}(2-|x|)^3 + \frac{1}{6}|x| - \frac{1}{3}, & 1 \le |x| < 2 \\ 0, & 2 \le |x| \end{cases} \quad (14)$$

III. RESULTS

Different interpolation methods have been applied to 15 cases from the Mini-MIAS database [19]. Each case includes signs of bilateral asymmetry and consists of left and right mammographic image in MLO view. Each image was segmented so the pectoral muscle and various artifacts outside the breast area were removed [20].

To quantitatively compare interpolation methods we used different mathematical similarity measures. The original image was compared with the image after computing forward and backward interpolation method.

The normalized 2-D cross-correlation coefficient *C* was used to assess image similarity [14]:

$$C = \left| \frac{\sum_{m,n} s(m,n) \cdot r(m,n) - M \cdot N \cdot \bar{s} \cdot \bar{r}}{\sqrt{\left(\sum_{m,n} s^2(m,n) - M \cdot N \cdot \bar{s}^2\right)\left(\sum_{m,n} r^2(m,n) - M \cdot N \cdot \bar{r}^2\right)}} \right| \quad (15)$$

where $\bar{s}$ and $\bar{r}$ are mean of the original and the twice interpolated image of the dimensions *M* x *N*, respectively. Maximal value that coefficient *C* can score is 1 which means that the images are identical.

Second measure that was used to evaluate interpolation methods was peak signal-to-noise ratio (PSNR):

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \tag{16}$$

where MSE is mean square error expressed as:

$$MSE = \frac{\sum_{m,n}\left[s(m,n) - r(m,n)\right]^2}{M \cdot N} \tag{17}$$

To evaluate interpolation quality we also used structural similarity (SSIM) index between two images [21]. When the two images are identical SSIM index is 1.

In our previous work, we have used B-spline interpolation and as an agreement we interpolated right breast to the size of the left breast [13]. In this evaluation of different interpolation methods we interpolated image with larger breast area to the size of the image with smaller breast area according to the points on the breast contour depicted in Fig. 1. In this way we did not add new values to the image.

Results of the quality evaluation using the normalized 2-D cross-correlation coefficient, PSNR and SSIM are presented in Table 1, Table 2 and Table 3, respectively. Each row represents a pair of mammographic images and columns represent obtained measure for each interpolation method. Shadowed are maximal and minimal values for each interpolation methods.

The results show that the differences between interpolation methods are not significant. However, cubic interpolation with 6 x 6 and 8 x 8 kernels introduce greater error than the other methods. All three measures show that the worst interpolation quality has cubic interpolation with kernel size of 8 x 8. According to the normalized 2-D cross-correlation coefficient and SSIM best interpolation method is B-spline. On the other hand, PSNR showed best results for the nearest neighbor interpolation. However, difference between results obtained with B-spline interpolation and with nearest neighbor interpolation is very small.

An example of visual quality of interpolation methods is shown in Fig. 2. Fig. 2 (a) shows segmented original mammographic image mdb108 from the Mini-MIAS database. Visual effect of interpolation methods on mammographic image is shown in Fig. 2 (b)-(i). Visual differences between most of the interpolation methods are negligible. Exceptions are six-point and eight-point cubic interpolation. They introduce errors due to kernel size which is also seen from the values of the mathematical similarity measures.

TABLE I. RESULTS OF EVALUATION OF INTERPOLATION METHODS USING NORMALIZED 2-D CROSS-CORRELATION COEFFICIENT

Interpolation method / Mini-MIAS case	Nearest neighbor	Bilinear	B-spline	Cubic 4x4, *a* = -1/2	Cubic 4x4, *a* = -3/4	Cubic 4x4, *a* = -1	Cubic 4x4, *a* = -1.3	Cubic 6x6	Cubic 8x8	O-Moms[3]	Cubic Schaum
mdb71 mdb72	0.99986392	0.99988261	0.99994552	0.99993199	0.99994032	0.99994224	0.99993191	0.99867277	0.99847348	0.99978761	0.99992459
mdb75 mdb76	0.99991212	0.99976884	0.99989991	0.99987206	0.99988682	0.99989214	0.99988044	0.99864094	0.99844537	0.99956055	0.99985115
mdb81 mdb82	0.99996346	0.99981507	0.99993340	0.99990772	0.99992194	0.99992704	0.99991380	0.99845833	0.99823091	0.99962434	0.99988926
mdb83 mdb84	0.99984554	0.99984129	0.99992500	0.99990816	0.99991838	0.99992093	0.99990917	0.99830794	0.99805703	0.99970553	0.99989600
mdb89 mdb90	0.99988886	0.99988690	0.99994608	0.99993406	0.99994078	0.99994255	0.99993487	0.99871931	0.99852885	0.99978741	0.99992519
mdb91 mdb92	0.99994618	0.99984419	0.99993987	0.99991904	0.99993128	0.99993570	0.99992508	0.99869442	0.99850232	0.99969264	0.99990520
mdb95 mdb96	0.99995494	0.99986215	0.99995630	0.99993660	0.99994771	0.99995163	0.99994184	0.99862494	0.99841934	0.99970430	0.99992230
mdb97 mdb98	1.00000000	0.99990234	0.99996790	0.99995463	0.99996039	0.99996039	0.99995122	0.99860341	0.99839200	0.99960844	0.99994310
mdb99 mdb100	0.99996773	0.99987457	0.99995754	0.99994132	0.99995024	0.99995241	0.99994063	0.99863577	0.99843118	0.99968217	0.99992671
mdb101 mdb102	0.99973259	0.99978008	0.99988422	0.99986402	0.99987640	0.99987965	0.99986570	0.99865088	0.99845984	0.99960105	0.99984858
mdb103 mdb104	0.99999683	0.99991724	0.99997688	0.99996478	0.99997139	0.99997270	0.99996321	0.99865335	0.99844759	0.99981039	0.99995462
mdb105 mdb106	0.99994366	0.99991319	0.99996464	0.99995408	0.99996029	0.99996201	0.99995494	0.99890479	0.99873975	0.99983197	0.99994599
mdb107 mdb108	0.99999462	0.99993182	0.99997630	0.99996615	0.99997164	0.99997297	0.99996582	0.99848071	0.99825105	0.99986254	0.99995992
mdb109 mdb110	0.99991476	0.99990715	0.99995826	0.99994823	0.99995410	0.99995549	0.99994780	0.99855348	0.99833442	0.99982263	0.99994019
mdb111 mdb112	1.00000000	0.99986337	0.99995351	0.99993384	0.99994476	0.99994904	0.99994083	0.99854315	0.99832560	0.99972537	0.99991923
Average	0.99992835	0.99986605	0.99994569	0.99992911	0.99993843	0.99994113	0.99993115	0.99860961	0.99840258	0.99972046	0.99991680

TABLE II. RESULTS OF EVALUATION OF INTERPOLATION METHODS USING PSNR IN [dB]

Interpolation method / Mini-MIAS case	Nearest neighbor	Bilinear	B-spline	Cubic 4x4, *a* = -1/2	Cubic 4x4, *a* = -3/4	Cubic 4x4, *a* = -1	Cubic 4x4, *a* = -1.3	Cubic 6x6	Cubic 8x8	O-Moms[3]	Cubic Schaum
mdb71 mdb72	48.17	48.81	52.14	51.18	51.75	51.89	51.17	29.10	28.54	46.23	50.73
mdb75 mdb76	50.71	46.51	50.15	49.08	49.61	49.82	49.37	29.71	29.15	43.72	48.42
mdb81 mdb82	54.10	47.05	51.49	50.07	50.80	51.09	50.37	28.52	27.96	43.97	49.28
mdb83 mdb84	46.16	46.04	49.30	48.42	48.93	49.07	48.47	26.57	26.01	43.36	47.88
mdb89 mdb90	48.26	48.19	51.40	50.53	51.00	51.13	50.58	28.40	27.83	45.45	49.98
mdb91 mdb92	53.60	48.98	53.12	51.83	52.54	52.83	52.16	30.61	30.05	46.03	51.14
mdb95 mdb96	52.92	48.07	53.06	51.44	52.28	52.61	51.81	28.80	28.24	44.75	50.56
mdb97 mdb98	Inf	47.81	52.64	51.14	51.73	51.81	50.82	25.70	25.14	41.78	50.16
mdb99 mdb100	53.90	48.00	52.71	51.30	52.02	52.21	51.25	28.32	27.76	43.97	50.34
mdb101 mdb102	45.94	46.78	49.57	48.87	49.29	49.40	48.92	29.86	29.30	44.20	48.41
mdb103 mdb104	65.07	50.90	56.44	54.61	55.52	55.72	54.42	29.61	29.04	47.30	53.51
mdb105 mdb106	50.33	48.45	52.35	51.22	51.85	52.04	51.30	25.81	25.25	45.58	50.51
mdb107 mdb108	59.56	48.53	53.12	51.57	52.34	52.55	51.53	25.62	25.06	45.49	50.84
mdb109 mdb110	49.03	48.66	52.13	51.19	51.72	51.85	51.16	27.40	26.84	45.85	50.57
mdb111 mdb112	Inf	46.92	51.60	50.07	50.85	51.20	50.55	27.30	26.74	43.89	49.20
Average	52.13	47.98	52.08	50.84	51.48	51.68	50.93	28.09	27.53	44.77	50.10

TABLE III. RESULTS OF EVALUATION OF INTERPOLATION METHODS USING SSIM

Interpolation method / Mini-MIAS case	Nearest neighbor	Bilinear	B-spline	Cubic 4x4, *a* = -1/2	Cubic 4x4, *a* = -3/4	Cubic 4x4, *a* = -1	Cubic 4x4, *a* = -1.3	Cubic 6x6	Cubic 8x8	O-Moms[3]	Cubic Schaum
mdb71 mdb72	0.9969	0.9968	0.9984	0.9981	0.9983	0.9983	0.9978	0.9526	0.9480	0.9941	0.9979
mdb75 mdb76	0.9983	0.9961	0.9983	0.9979	0.9981	0.9982	0.9977	0.9755	0.9728	0.9925	0.9975
mdb81 mdb82	0.9992	0.9948	0.9982	0.9975	0.9979	0.9979	0.9971	0.9730	0.9698	0.9893	0.9970
mdb83 mdb84	0.9953	0.9938	0.9971	0.9965	0.9969	0.9969	0.9961	0.9346	0.9278	0.9884	0.9960
mdb89 mdb90	0.9968	0.9967	0.9985	0.9982	0.9984	0.9983	0.9979	0.9578	0.9538	0.9936	0.9979
mdb91 mdb92	0.9990	0.9966	0.9986	0.9982	0.9984	0.9985	0.9980	0.9891	0.9879	0.9934	0.9979
mdb95 mdb96	0.9985	0.9960	0.9987	0.9981	0.9984	0.9984	0.9979	0.9539	0.9492	0.9917	0.9977
mdb97 mdb98	1.0000	0.9939	0.9980	0.9970	0.9975	0.9976	0.9967	0.9798	0.9775	0.9877	0.9965
mdb99 mdb100	0.9988	0.9962	0.9987	0.9982	0.9984	0.9984	0.9979	0.9707	0.9675	0.9920	0.9978
mdb101 mdb102	0.9966	0.9964	0.9981	0.9978	0.9980	0.9980	0.9976	0.9678	0.9644	0.9931	0.9976
mdb103 mdb104	0.9999	0.9972	0.9992	0.9988	0.9990	0.9990	0.9985	0.9630	0.9590	0.9935	0.9984
mdb105 mdb106	0.9974	0.9942	0.9976	0.9968	0.9972	0.9973	0.9966	0.9590	0.9546	0.9894	0.9963
mdb107 mdb108	0.9996	0.9956	0.9984	0.9978	0.9981	0.9981	0.9975	0.9846	0.9828	0.9912	0.9974
mdb109 mdb110	0.9969	0.9952	0.9978	0.9973	0.9976	0.9976	0.9970	0.9239	0.9171	0.9908	0.9969
mdb111 mdb112	1.0000	0.9956	0.9986	0.9979	0.9983	0.9983	0.9976	0.9822	0.9801	0.9910	0.9975
Average	0.9982	0.9957	0.9983	0.9977	0.9980	0.9980	0.9975	0.9645	0.9608	0.9914	0.9974

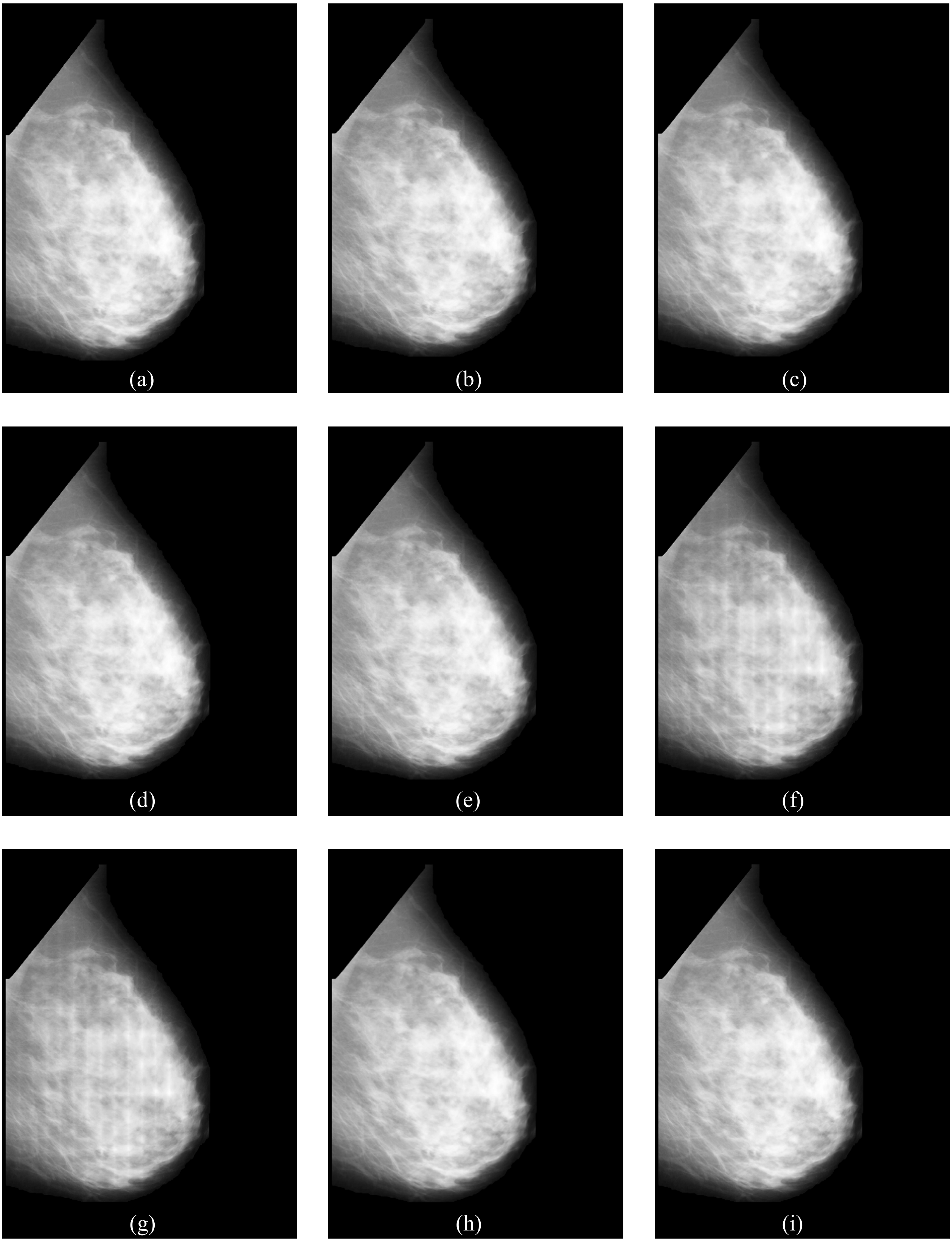

Figure 2. Segmented mammographic image mdb108: (a) original; (b) nearest neighbor interpolation; (c) bilinear interpolation; (d) B-spline intrepolation; (e) cubic interpolation with kernel size 4 x 4 and *a* = -1/2; (f) cubic interpolation with kernel size 6 x 6; (g) cubic interpolation with kernel size 8 x 8; (h) o-Moms^3 interpolation; (i) Schaum interpolation.

IV. CONCLUSION

Alignment of left and right breast in mammographic images is often first step in bilateral asymmetry detection. Alignment can be done using interpolation method according to breast landmarks. We have evaluated different interpolation methods using three mathematical similarity measures: normalized 2-D correlation coefficient, PSNR and SSIM. From the obtained results we can conclude that the best methods for use with mammographic images is B-spline interpolation and nearest neighbor interpolation. The worst performance showed cubic interpolation with kernel size of 6 x 6 and 8 x 8. In future work we plan to develop a method for differential analysis between corresponding regions in aligned left and right breasts.

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