Triple-Link Fusion Decision Method for Through-the-Wall Radar Human Motion Recognition

Weicheng Gao, Xiaopeng Yang, Tian Lan, Xiaodong Qu and Junbo Gong

May 28, 2022
Abstract—To better solve the accuracy degradation of human motion recognition due to low signal-to-clutter-plus-noise ratio (SCNR) and low resolution of through-the-wall radar (TWR) imaging, a triple-link fusion decision human motion recognition method for through-the-wall radar is proposed in this paper. This method combines the physical information, visual local information and visual global information in imaging. Specifically, the idea of complementarity of three weak models, including empirical modal decomposition (EMD) algorithm based on statistic signal detection, visual gradient-level based kernel method and visual regionalized macro-level based shuffle attention improved residual neural network (SA-Inception-ResNet) algorithm are introduced in the method, and the Dempster-Shafer (D-S) synthesis theory is used to achieve decision level fusion recognition. The final results are inferred by an adaptive boosting method on the trained weak models and the fused strong model. Experiments are carried out to demonstrate that the accuracy of the algorithm exceeds 99.54%, while the prediction performance and robustness are significantly improved compared with previous methods.

Index Terms—through-the-wall radar, human target recognition, micro-Doppler signature, fusion detection theory

I. INTRODUCTION

WITH the advantages of ultra-wideband (UWB) signals with certain medium penetration capability and better resolution for close targets, through-the-wall radar (TWR) technology has been rapidly developed in the past decades. It can better serve various fields such as military radar counter-terrorism and civilian radar disaster prevention and control. To cope with the extended moving target identification problem of through-the-wall radar, we need to propose a classification algorithm with high accuracy and robustness, and combine existing clutter and noise suppression and data argumentation methods to build a complete through-the-wall radar system.

Existing human moving target identification results for through-wall radar can be classified into three categories. The first category of methods is based on traditional physical modeling and statistical signal processing theory, including singular value decomposition (SVD) [1], truncated singular value decomposition (TSVD) [2], through-the-wall body direction estimation algorithm (DDOA) and improved Kalman filtering methods [3]. These methods are based on physical models, which have low computational complexity and are the most interpretable, but have poor generalization capability and are not applicable to complex scenarios [1]. The second class of methods is based on compressed sensing and sparse modeling theory, including robust principal component analysis (RPCA) based on micro-Doppler features [4], support vector machines (SVM) [5] and likelihood ratio test (LRT) detectors [6], a pure time delay (TDOE) estimation method based on an orthogonal matched tracking (OMP) algorithm [7] and a cross-validation based simultaneous orthogonal matched tracking algorithm (CV-CSOMP) [8]. These methods have better recognition results than the first class of traditional methods, but still have limited generalization capability and performance in dealing with complex motion state scenes [5]. The third class of methods is based on the new generation of AI theory, including autoencoder networks (AEN) [9], convolutional neural networks (CNN) [10], generative adversarial networks (GAN) [11], and fully connected multilayer perceptrons (MLP) [12]. Artificial intelligence algorithms have powerful algorithmic capabilities, but consume significant computational costs. Despite the advantages and disadvantages of each of the three approaches, few articles have fused the...
information from the physical, visual microscopic and visual macroscopic layers targeted by the three types of approaches to achieve complementary advantages for them [10].

In this paper, we propose a three-level information complementation algorithm for identifying the motion state of human targets behind a wall for decision-level link fusion and give a system design. Experiments demonstrate that the final accuracy of the fusion verdict exceeds 99.54%, and the accuracy of the fusion verdict of the remaining links remains above 96% even if any one of them fails during the system deployment, making the accuracy and robustness of the system greatly optimized relative to previous results.

The remainder of this paper is organized as follows. The TWR signal model and processing system design are briefly discussed in Section II, followed by triple-link fusion decision theory analysis in Section III. The experimental results and discussions are given in Section IV. Finally, the conclusion is given in Section V.

II. SYSTEM MODEL

A. General Flow Chart for TWR Human Motion Recognition

In Fig. 1, we present a flowchart of a human moving target detection system based on a single-transmit, single-receive through-the-wall radar. The back projection (BP) algorithm of the step-frequency UWB radar system is used to achieve cumulative imaging of human moving targets. First we performed wall clutter suppression and noise cancellation, and used wavelet scattering networks (WSN) for data feature argumentation. The classifier proposed by the back-end recognition algorithm contains three different decision links. First, we will give the micro-Doppler modeling of the human motion. Then the empirical mode decomposition (EMD) algorithm is used to process the human micro-Doppler modeling signal. The differences in the modal power spectrum distribution of the micro-Doppler signals are used to distinguish the human behavior and the classical Bayesian judgment algorithm is used to give the recognition results. The second link will give the micro histogram of oriented gradient (HOG) features of the imaged information and use a kernel function based classifier to form probability scores for different human behaviors. The third link will focus on the macroscopic features of the imaging. To achieve this goal, we propose a ResNet algorithm based on shuffle attention improvement (SA-Inception-ResNet) and form recognition score scoring for different human behaviors. Finally, we propose to use Dempster-Shafer (D-S) evidence theory at the decision level to fuse the degree of scoring of the three segments to obtain the output of the system. In the next subsection, we will dive into the mathematical modeling theory of the algorithm.

B. Signal Model and Data Pre-processing

The stepper frequency is used as the transmit signal of the radar, expressed as

\[
s(t) = \sum_{k=0}^{K-1} \text{rect} \left( \frac{t}{T} - \frac{1}{2} - k \right) e^{2\pi j f_0 + k \Delta f} t
\]  

(1)

where \(f_0\) represents the starting frequency of the stepper frequency. \(\Delta f\) represents the step frequency interval, and

\[
\text{rect}(t) = \begin{cases} 
1, & t \in \left[ -\frac{1}{2}, \frac{1}{2} \right] \\
0, & t \in (\infty, -\frac{1}{2}) \cup \left( \frac{1}{2}, \infty \right)
\end{cases}
\]

The received signal can thus be expressed as

\[
S_r(t) = \sum_{p=1}^{P} a_p s(t - \tau_p) + S_w(t) + S_n(t)
\]

(2)

where \(S_w(t)\), \(S_n(t)\) represents the wall effect and noise. \(a_p\) represents the echo gain ratio at the \(p^{th}\) point. \(\tau_p\) is the time delay. Assume \(\phi_r\) is the echo matrix. Clutter and noise suppression of the received signal using SVD method to obtain

\[
\phi_r = USV^H = \sum_{i\in W}^z \phi_i + \sum_{i\in T}^z \phi_i + \sum_{i\in N}^z \phi_i
\]

(3)

where \(\phi_i\) represents the singular values of the echo matrix. \(\phi_i\) and \(v_i\) represent the left and right vectors and \(H\) denotes the Hermitian transpose. \(\phi_r\) is a \(N \times M\) matrix. For changeable constant \(\alpha\), solve the following optimization problem

\[
\delta_d = E(\delta_i) - \alpha \sqrt{D(\delta_i)}
\]

(4)

\[
\min \text{AIC} = \text{NIlog} \left( \frac{\sum_{i=1}^{M} \sigma_i u_i \bar{v}_i^H}{\prod_{m=1+i}^{M} \sigma_m} \right) M - i
\]

(5)

\[
+ \frac{1}{2}(2M - i)i \log N
\]

For those singular values \(\delta_i < \delta_d\) and \(\sigma_i > \sigma_m\), we think of them as clutter and noise subspace respectively, which should be set to zero. After that we use wavelet scattering network to enhance the data features, where the wavelet transform is defined as \(WT(a, \tau) = \int_{-\infty}^{\infty} f(t) \psi(\frac{t - \tau}{a}) dt\), \(f(t)\) measures the time domain representation of the signal. \(\psi\) represents the wavelet transform basis functions, which is Morlet function here.

As shown in Fig. 2, the \(j^{th}\) layer and the convolutional basis function corresponding to each layer of the wavelet scattering network can be expressed respectively as

\[
\psi_j(x) = 2^{-2j} \psi(2^{-j}x)
\]

(6)

\[
\psi_{l,x}(x) = 2^{-2i} \psi(2^{-i}r_0x)
\]

(7)

where \(k = \log_2 L\) represents the logarithm of the scale transform coefficient \(L\) in the wavelet transform. \(x\) represents the input of the node in the WSN. Define \(\theta\) as the rotation angle of the wavelet transform in WSN, then

\[
r_\theta = \begin{bmatrix}
\cos \theta & -\sin \theta \\
\sin \theta & \cos \theta
\end{bmatrix}
\]

(8)
The final output we get is

\[ \phi_{WSN,j} = \begin{bmatrix} \phi \ast \psi_{2j} \\ \phi_1 \ast \psi_{2j} \\ \phi_2 \ast \psi_{2j} \end{bmatrix} \quad 1 \leq j \leq L \quad (9) \]

where \( j \) represents the total number of the scaling. \( \phi \ast \psi_{2j} \) provides information on the average energy distribution. \( \phi_1 \ast \psi_{2j} \) is an enhanced scale-invariant feature transform (SIFT) feature vector representation. In order to achieve the best imaging data enhanced contrast information, we experimentally chose \( \theta = 1.5708^\circ \) as the condition for subsequent processing.

### III. Triple-link Fusion Decision Algorithm

Our proposed algorithm includes three decision links. In the first session, we first extract the micro-Doppler information of the human target. After STFT,

\[ S_r = S_T + S_W + S_N \quad (10) \]

For the frequency point \( f_c \) the corresponding denoised micro-Doppler expression is

\[
S_{r, \text{Denoise}} = a_w \cos [2\pi f_c t + \varphi_w] \\
+ a_T (t - \tau_p) \cos [2\pi f_c (t - \tau_p) + \varphi_T(t)] \quad (11)
\]

After coherent demodulation,

\[
S_{r', \text{Denoise}} = a_w \cos (\varphi_w) + a_T (t - \tau_p) \cos (\varphi_T(t)) \quad (12)
\]

The process of our proposed micro-Doppler feature based EMD algorithm can be expressed as solving \( \max \) \( X(p) \), \( \min \) \( X(q) \), finding a series the envelope \( x_{\text{max}}(t) \) and \( x_{\text{min}}(t) \) using the Lagrange interpolation formula, then define

\[
m(t) = \frac{1}{2} [X_{\text{max}}(t) + X_{\text{min}}(t)] \quad (13)
\]

If \( E(m(t)) = 0 \) and The difference between the number of over-zero points and the number of extreme values \( \leq 1 \), then record \( X(t) \) at this point as \( IMFI_k(t) \). Else,

\[
X(t) = X(t) - m(t) \\
X_k(t) = X_{k-1}(t) - IMFI_k(t) \quad (14)
\]

Bayes decision is used to classify the modal power distribution information, as

\[
\lambda_{ij} = \begin{cases} 0, & \text{if } i = j \\ 1, & \text{otherwise} \end{cases}
\]

\[
R(c_i \mid IMFSample) = \sum_{j=1}^{N} \lambda_{ij} P(c_j \mid IMFSample) = 1 - P(c \mid IMFSample) \quad (15)
\]

where,

\[
h^{IMF}(IMFSample) = \arg \max_{c \in Y} P(c \mid IMFSample) \quad (16)
\]

In the second link, we first obtain the HOG features by computing the gradient values of the unfolding vector of the distance image as \( G_x(x, y) = I(x+1, y) - I(x-1, y), G_y(x, y) = \)
\[ I(x, y+1) - I(x, y-1), G(x, y) = \sqrt{G_x(x, y)^2 + G_y(x, y)^2}, \]
\[ \theta(x, y) = \arctan \left( \frac{G_y(x, y)}{G_x(x, y)} \right). \]
And then the identification and classification of HOG feature vectors is performed using the kernel function improved SVM classifier, which can be specifically expressed as solving the following optimization problem

\[
\max_{\alpha} \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \tag{18}
\]
\[
\text{s.t.} \sum_{i=1}^{m} \alpha_i y_i = 0, 0 \leq \alpha_i \leq C, i = 1, \ldots, m
\]

where \( K \) is the kernel function. The output result can be expressed as

\[
f(x) = \sum_{i=1}^{m} \alpha_i y_i K(x_i, x) + b \tag{19}
\]

where \( \alpha_i \) and \( b \) can be obtained by sample training. Because the through-the-wall imaging data is sparse and the introduced noise in the imaging information can be modeled approximately using Gaussian noise due to the effect of the wall. Therefore radial basis function (RBF, also known as Gaussian function) \( K(x_i, x_j) = \exp \left( -\frac{\|x_i - x_j\|^2}{2\sigma^2} \right) \) is the best choice of the kernel function, where \( \sigma > 0 \) represents the bandwidth.

In the third link, we learn and reason directly on the wavelet scattering network enhanced data using a shuffle attention improved ResNet to finally obtain macroscopic information about the visual aspects of the imaging. Among them, the structure of the proposed replacement attention mechanism is shown in Fig. 3.

![Block diagram of the improved structure of the shuffle attention.](image)

Fig. 3. Block diagram of the improved structure of the shuffle attention.

At the back end of the three links we use D-S evidence theory for decision level scoring vector fusion. Define the mass function as a mapping function on this recognition framework satisfying \( m : \mathcal{Z}^{Output} \rightarrow [0, 1], m(\emptyset) = 0 \), and \( \sum_{A \subseteq \mathcal{Z}^{Output}} m(A) = 1 \), where \( A \) is the focal elements that \( m(A) > 0 \). \( A \) represents the triple-link output decision space. The normalization factor is \( K = \sum_{A_1 \cap A_2 \cap A_3 \neq \emptyset} m_1(A_1) \cdot m_2(A_2) \cdot m_3(A_3) \). The DS output fusion decision result can be expressed as

\[
\frac{1}{K} \sum_{A_1 \cap A_2 \cap A_3 = A} m_1(A_1) \cdot m_2(A_2) \cdot m_3(A_3) \tag{20}
\]

Which is also the final result. Algorithm 1 shows the complete block diagram of the proposed triple-link algorithm.

**Algorithm 1: Triple-link Fusion Decision Algorithm**

**Input:** Training datas \( \mathbf{x} \) with labels \( \mathbf{y} \): \( (x_1, y_1), \ldots, (x_m, y_m) \) where \( x_i \in X, y_i \in Y = \{ K \text{ categories} \} \).

**Output:** Final model: \( F(x) \).

1. \( M = 3; \)
2. \( T^{(1)}(x) = \text{Bayes - IMF}(x), \) by solving: \( \text{IMF}(x), \quad R(c_i \mid \text{IMF Sample}) = \sum_{i=1}^{N} \lambda_i P(c_i \mid \text{IMF Sample}) \), where \( R(c \mid \text{IMF Sample}) = 1 - P(c \mid \text{IMF Sample}) \), \( h^{\text{IMF}}(\text{IMF Sample}) = \max_{c \in Y} P(c \mid \text{IMF Sample}); \)
3. \( T^{(2)}(x) = f(x), \) by solving: \( \text{HOG feature extraction for } x \text{ and } y, \) and \( \max_{\alpha} \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \) s.t. \( \sum_{i=1}^{m} \alpha_i y_i = 0, 0 \leq \alpha_i \leq C, i = 1, \ldots, m, \) and \( f(x) = \sum_{i=1}^{m} \alpha_i y_i K(x_i, x) + b; \)
4. \( T^{(3)}(x) = \text{SA - Inception - ResNet}(X); \)
5. \( T^{(\text{fus})}(x) = \frac{1}{K} \sum_{X_1 \cap X_2 \cap X_3 = X} T^1(X_1) \cdot T^2(X_2) \cdot T^3(X_3); \)
6. for \( m \) from 1 to \( M \) do
7. Generate \( T^{(m)}(x) \) using weights \( w_i \) and datas.;
8. \( \text{err}^{(m)} = \frac{\sum_{i=1}^{n} w_i^{(m)} (c_i \neq T^{(m)}(x_i))}{\sum_{i=1}^{n} w_i^{(m)} }; \)
9. \( \alpha^{(m)} = \log \frac{1 - \text{err}^{(m)}}{\text{err}^{(m)}} + \log (K - 1); \)
10. \( w_i \leftarrow w_i \cdot \exp \left( \alpha^{(m)} \cdot I \right) \), \( i = 1 \) to \( n; \)
11. Re-normalize and fine-tune \( w_i \) by comparing: \( T^{(\text{fus})}(x) \) with \( T^{(m)}(x) \) with \( T(x) = \sum_{m=1}^{M} \sum_{i=1}^{n} w_i T^{(m)}(x_i) / M \sum_{i=1}^{n} w_i; \)
12. end
13. \( F(x) = \arg \max_{x} \sum_{m=1}^{M} \alpha^{(m)} \cdot I \left( T^{(m)}(x) = k \right); \)

**IV. EXPERIMENTAL RESULTS**

In the field experiments, as shown in Fig. 4 and TABLE I, the output echo matrix \( \phi_i \) represents the human target imaging information after wall clutter and noise subspace cancellation and the results of WSN data argumentation are shown in Fig. 5.

In the first link, the micro-Doppler empirical mode decomposition is performed for the unoccupied scene behind the wall, the stationary scene of the human body, and the moving scene of the human body, respectively, to obtain the power distribution shown in Fig. 6. The IMF data generated after EMD is collected by Hilbert transform, and the instantaneous frequency of the resolved signal can be used to obtain our estimate of the micro-Doppler shift by using its intersection
### TABLE I

**EXPERIMENTAL SYSTEM PARAMETERS SETTING**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Antenna transceiver spacing</td>
<td>(Single-transmitter-single-receiver) 0.15 m</td>
</tr>
<tr>
<td>Work center frequency</td>
<td>1.5 GHz</td>
</tr>
<tr>
<td>Pulse width</td>
<td>2 ns</td>
</tr>
<tr>
<td>Sampling points</td>
<td>2048</td>
</tr>
<tr>
<td>Pulse repetition frequency</td>
<td>0.4 MHz</td>
</tr>
<tr>
<td>Sampling period</td>
<td>4 s</td>
</tr>
<tr>
<td>Wall thickness</td>
<td>0.24 m</td>
</tr>
<tr>
<td>Human range of motion</td>
<td>3 ∼ 8 m</td>
</tr>
<tr>
<td>Human movement state</td>
<td>θ</td>
</tr>
<tr>
<td>Antenna to ground scale (Antenna pitch/Height)</td>
<td>0.1</td>
</tr>
</tbody>
</table>

![Fig. 4](image4.png)

Fig. 4. Experimental scenes: (a) geometric scenes of antenna, human motion and data acquisition and (b) photographs of the experimental site.

![Fig. 5](image5.png)

Fig. 5. Effects after SVD clutter and noise removal and WSN data argumentation under changing different rotation angle θ: (a) no human behind a wall, (b) stationary human target behind a wall and (c) walking human target behind a wall.

![Fig. 6](image6.png)

Fig. 6. IMF spectrum after EMD decomposition with the scenes of (a) no human targets, (b) human standing and (c) human walking.

function $\theta(t)$ to derive the derivative of $t$. The final IMF data are exponentially distributed for different modes of high, medium and low, which can give judgments for different motion states. In the second link, the image is divided into several cells, each containing 8 X 8 = 64 pixels, with no overlap between adjacent cells. In our experiments, we map the data information to a 256 X 256 imaging space, so that the total number of cells is 32 X 32 = 1024. Within each cell, the histogram of gradient directions is counted, and all gradient directions are divided into 9 feature vectors as the horizontal axis of the histogram, and the cumulative values of the gradient values corresponding to the angle range as the vertical axis of the histogram. L2 normalization is performed on all histograms and all feature vectors are combined to form the HOG features we need for imaging information. This HOG feature data is used as the input to the kernel function classifier, and the probabilities of judgments for various human behavior states are used as the output. In the third link we train the proposed SA-Inception-ResNet shown in Fig. 7 in APPENDIX and fuse the output of the last fully connected layer in ResNet as the scoring result with the first two output information for D-S fusion decision.

We subdivide the human body at rest behind the wall and the human motion behind the wall into parallel, vertical and overhead categories based on their orientation relative to the radar, combined with unmanned scenes, for a total of seven different classification labels. The validation confusion matrix of the algorithm on our experimental dataset is plotted separately in Fig. 8, when only one of the three links is in operation, Fig. 10, when fusion decision is in operation and Fig. 9, when one of the three links fails, which can be found in APPENDIX.

TABLE II and TABLE III represent the effect of fusion decision when improving different kinds of kernel functions in the second link and different kinds of attention mechanism neural networks in the third link. From this, we verify that our proposed combined scheme of radial basis function (RBF)
TABLE II
JUDGEMENT ACCURACY USING TEN DIFFERENT KERNEL FUNCTIONS IN THE SECOND LINK

<table>
<thead>
<tr>
<th>Name of the Kernel Function</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear Kernel</td>
<td>78.94%</td>
</tr>
<tr>
<td>Polynomial Kernel</td>
<td>87.96%</td>
</tr>
<tr>
<td>Radial Basis Function (RBF, Gaussian Kernel)</td>
<td>94.21%</td>
</tr>
<tr>
<td>Exponential Kernel</td>
<td>88.89%</td>
</tr>
<tr>
<td>Laplacian Kernel</td>
<td>90.28%</td>
</tr>
<tr>
<td>ANOVA Kernel</td>
<td>84.26%</td>
</tr>
<tr>
<td>Rational Quadratic Kernel</td>
<td>89.35%</td>
</tr>
<tr>
<td>Multiquadric Kernel</td>
<td>85.88%</td>
</tr>
<tr>
<td>Inverse Multiquadric Kernel</td>
<td>92.13%</td>
</tr>
<tr>
<td>Sigmoid Kernel</td>
<td>82.18%</td>
</tr>
</tbody>
</table>

TABLE III
JUDGEMENT ACCURACY USING EIGHT DIFFERENT ATTENTION MECHANISM BASED NEURAL NETWORKS IN THE THIRD LINK

<table>
<thead>
<tr>
<th>Name of the Neural Networks</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>GoogleNet-Inception-V1</td>
<td>89.58%</td>
</tr>
<tr>
<td>GoogleNet-Inception-V2</td>
<td>90.27%</td>
</tr>
<tr>
<td>GoogleNet-Inception-V3</td>
<td>92.36%</td>
</tr>
<tr>
<td>GoogleNet-Inception-V4</td>
<td>93.75%</td>
</tr>
<tr>
<td>Xception41</td>
<td>92.82%</td>
</tr>
<tr>
<td>Xception65</td>
<td>95.14%</td>
</tr>
<tr>
<td>Inception-ResNet-V1</td>
<td>93.51%</td>
</tr>
<tr>
<td>SA-Inception-ResNet</td>
<td>95.60%</td>
</tr>
</tbody>
</table>

Based on the kernel function for the second link and improved ResNet with SA module for the third link, the proposed algorithm performs better than any method when considered separately. In general, the proposed algorithm can be very effectively applied to the through-the-wall radar human dynamic and static behavior recognition scenario, and effectively improve the accuracy and robustness.

V. CONCLUSION

In this paper, combining the physical information, visual local information and visual global information in imaging, a human motion recognition algorithm for through-the-wall radar based on triple-link fusion decision is proposed. The Bayesian decision theory with nested EMD algorithms, kernel methods with a nested HOG feature extraction, and artificial residual neural networks with shuffle attention mechanism, respectively, is applied. Finally, the D-S evidence theory is employed to combine the decision information from the three links to achieve the final human motion pattern decoding results. Experiments have been given to show that the algorithm’s accuracy reaches 99.54% and that prediction performance and resilience are greatly improved over earlier researches. Our future work will focus on the study of human motion data argumentation and recognition algorithms for single and multiple dimensioned through-the-wall radar.

APPENDIX

Graphical representation of experimental data and results from Figure 7 to Figure 10

![Graphical representation of experimental data and results](image)

Fig. 7. Visualization of SA-Inception-ResNet training and validation process: (a) training accuracy curve, (b) training loss function curve, (c) validation accuracy curve and (d) validation loss function curve.
Fig. 8. Confusion matrix for single-link judgments: (a) first link: micro-Doppler features with EMD method, (b)second link: HOG features with kernel method and (c)third link: SA-Inception-ResNet method.

Fig. 9. Confusion matrix in case of failure of a link deployment: (a) third link deployment failure, (b) second link deployment failure and (c) first link deployment failure.

Fig. 10. Confusion matrix for the experimental result of triple-link fusion decision making algorithm.